A Review of Edge AI Vision Systems for Automated Waste Classification and Material Recovery

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ABSTRACT

The growing volume of municipal solid waste has increased the need for efficient and automated material recovery systems. Recent advances in artificial intelligence, computer vision, and edge computing have enabled waste materials to be classified and sorted directly at the point of disposal. This paper reviews recent developments in low-cost Edge AI vision systems for automated waste classification, with particular emphasis on deep learning models, embedded processing platforms, and mechanical sorting mechanisms. Existing studies on Convolutional Neural Networks (CNNs), MobileNet-based architectures, traditional machine learning algorithms, Raspberry Pi platforms, TensorFlow Lite, and computer vision techniques are examined and compared. The literature indicates that deep learning models generally provide higher classification accuracy than traditional machine learning approaches, while lightweight architectures such as MobileNetV2 offer a more practical balance between accuracy, inference time, memory usage, and power consumption for embedded deployment. However, differences in datasets, waste categories, testing conditions, and evaluation procedures limit direct comparison between reported results. Several challenges also remain, including dataset imbalance, visually similar materials, lighting variation, contaminated or overlapping waste, limited processing resources, and insufficient integration between classification models and physical sorting mechanisms. Based on the reviewed studies, this paper identifies the need for a low-cost and fully integrated Edge AI system that combines lightweight visual classification, local processing, and automated mechanical sorting. The findings provide a practical reference for developing scalable waste-classification systems for households, educational institutions, and other small-scale material recovery applications.

Keywords: Automated waste classification, computer vision, deep learning, Edge AI, material recovery, Raspberry Pi, smart waste management.

INTRODUCTION

The continuous growth of municipal solid waste (MSW) has become a major environmental, economic, and public-health concern worldwide. Rapid urbanization, population growth, changing consumption patterns, and increased use of disposable products have contributed to a substantial rise in waste generation. According to the United Nations Environment Programme, global MSW generation is projected to increase from approximately 2.1–2.3 billion tons in 2023 to 3.8 billion tons annually by 2050 (UNEP, 2024). Improperly managed waste can contaminate soil and water, contribute to air pollution through open burning, and increase greenhouse gas emissions from landfills. These challenges highlight the need for more efficient waste segregation and material recovery strategies that support the circular economy and sustainable urban development.

Effective waste segregation is essential because the recovery value of recyclable materials depends heavily on the purity of the separated waste stream. However, conventional waste segregation continues to rely considerably on manual labor. Manual sorting is time-consuming, inconsistent, and exposes workers to sharp objects, contaminated materials, harmful substances, and biological hazards (Ahmad et al., 2025; Fotovvatikhah et al.,

2025). The efficiency of manual separation may also decline because of fatigue, variations in human judgement, and the increasing volume and diversity of discarded materials. Consequently, recyclable items may be incorrectly classified or contaminated by organic and non-recyclable waste, reducing their suitability for further processing.

Artificial intelligence (AI) and computer vision have emerged as promising technologies for addressing the limitations of conventional waste segregation. Camera-based systems can analyze visual characteristics such as color, shape, texture, and surface patterns to distinguish between different types of waste. Traditional machine learning algorithms, including Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Decision Tree, and Random Forest, have been applied to waste-classification tasks. However, these approaches commonly depend on manually selected features and may experience difficulty when waste objects are presented under uncontrolled lighting, complex backgrounds, occlusion, or physical contamination (Ahmad et al., 2025; Fotovvatikhah et al., 2025).

Deep learning, particularly Convolutional Neural Networks (CNNs), has improved visual waste classification by automatically learning relevant features directly from image data. Architectures such as ResNet and DenseNet have demonstrated high classification performance in controlled experimental environments (Fotovvatikhah et al., 2025; Mia et al., 2025). Nevertheless, these models typically require considerable processing power, memory, and energy, which can restrict their deployment on low-cost embedded platforms. Furthermore, accuracy reported using a controlled or balanced dataset may not represent performance in real waste-management environments, where objects can be dirty, damaged, overlapping, partially visible, or visually similar.

Edge AI offers a practical approach by performing AI inference locally on embedded devices rather than relying entirely on remote cloud servers. Platforms such as the Raspberry Pi can be integrated with cameras, sensors, and electromechanical actuators to create compact and relatively low-cost waste-sorting systems (Mia et al., 2025; Vanitha et al., 2025). Local processing can reduce network dependency and communication delay while improving operational continuity in locations with limited Internet connectivity. Lightweight CNN architectures such as MobileNetV2, together with optimization frameworks such as TensorFlow Lite, are particularly relevant because they offer a practical balance between classification performance and computational requirements for embedded deployment (Fotovvatikhah et al., 2025; Vanitha et al., 2025).

However, visual identification alone does not constitute a complete automated material recovery system. The classification output must be synchronized with a physical mechanism capable of directing the identified item into the correct receptacle. Existing prototypes have employed servo-controlled flaps, conveyor belts, and robotic arms for physical waste separation (Mia et al., 2025; Srinevasan et al., 2024; Vanitha et al., 2025). Although robotic arms may offer greater flexibility and positioning accuracy, they generally involve higher cost, mechanical complexity, control requirements, and power consumption. In contrast, servo-controlled flaps can provide a simpler solution for household, educational, and small institutional applications. The overall performance of an automated sorting system therefore depends not only on classification accuracy but also on inference time, actuator response, mechanical reliability, energy consumption, and system cost.

Despite growing research in AI-based waste classification, several limitations remain. Differences in datasets, waste categories, class distributions, testing environments, hardware platforms, and evaluation procedures make direct comparison between reported results difficult (Fotovvatikhah et al., 2025). Many studies evaluate classification models using clean and individually positioned waste objects, whereas real waste streams contain contaminated, deformed, and overlapping materials. Other studies focus mainly on software performance without sufficiently evaluating the integration between image acquisition, embedded inference, sensors, and mechanical sorting. In addition, comprehensive reviews that jointly examine lightweight vision models, low-cost Edge AI platforms, and automated sorting mechanisms for small-scale applications remain limited.

Therefore, this paper reviews recent developments in low-cost Edge AI vision systems for automated waste classification and material recovery. The review focuses on three interconnected elements: AI and computer-vision algorithms for waste recognition, embedded platforms and optimization techniques for local inference,

and mechanical mechanisms for automated material separation. It compares the strengths, limitations, and practical suitability of the reviewed approaches while highlighting challenges related to datasets, environmental variability, computational constraints, and system integration. The findings are intended to provide a practical foundation for the future development of affordable and scalable automated waste-classification systems for households, educational institutions, and other small-scale material recovery applications.

LITERATURE REVIEW

2.1 Overview of Intelligent Waste Classification System

Intelligent waste classification systems combine image acquisition, artificial intelligence, embedded processing, and mechanical actuation to identify and separate waste materials. A typical system captures an image of a waste item using a camera, preprocesses the image, classifies it using a machine learning or deep learning model, and transmits the classification output to a sorting mechanism. Depending on the application, the mechanism may consist of a servo-controlled flap, conveyor belt, or robotic arm that directs the waste into the appropriate container (Deebika et al., 2026; Mia et al., 2025; Srinevasan et al., 2024; Vanitha et al., 2025).

Earlier waste-classification systems commonly employed traditional machine learning algorithms such as Support Vector Machine, k-Nearest Neighbor, Decision Tree, and Random Forest. Although these algorithms are relatively simple and computationally efficient, their performance depends heavily on the quality of manually extracted features. Recent studies have increasingly adopted Convolutional Neural Networks because these models can automatically learn visual features such as color, texture, shape, and object boundaries from waste images (Ahmad et al., 2025; Fotovvatikhah et al., 2025).

Deep CNN architecture can provide high classification performance but may require substantial memory and computational resources. Consequently, lightweight models such as MobileNet and MobileNetV2 have gained attention for Edge AI applications. These models can be optimized using TensorFlow Lite and deployed on embedded devices such as the Raspberry Pi, enabling classification to be performed locally without continuous dependence on cloud computing (Deebika et al., 2026; Fotovvatikhah et al., 2025). Nevertheless, the practical effectiveness of an intelligent waste-management system depends on more than the reported classification accuracy. The system must also operate reliably under environmental variation, process images within an acceptable time, and correctly coordinate its classification output with the physical sorting mechanism.

The evolution of computational methods used in automated waste-segregation systems is illustrated in Figure 1. The development has progressed from conventional machine-learning algorithms to deep-learning and transfer-learning approaches, followed by integrated hybrid systems that combine artificial intelligence with sensors, robotics and IoT technologies.

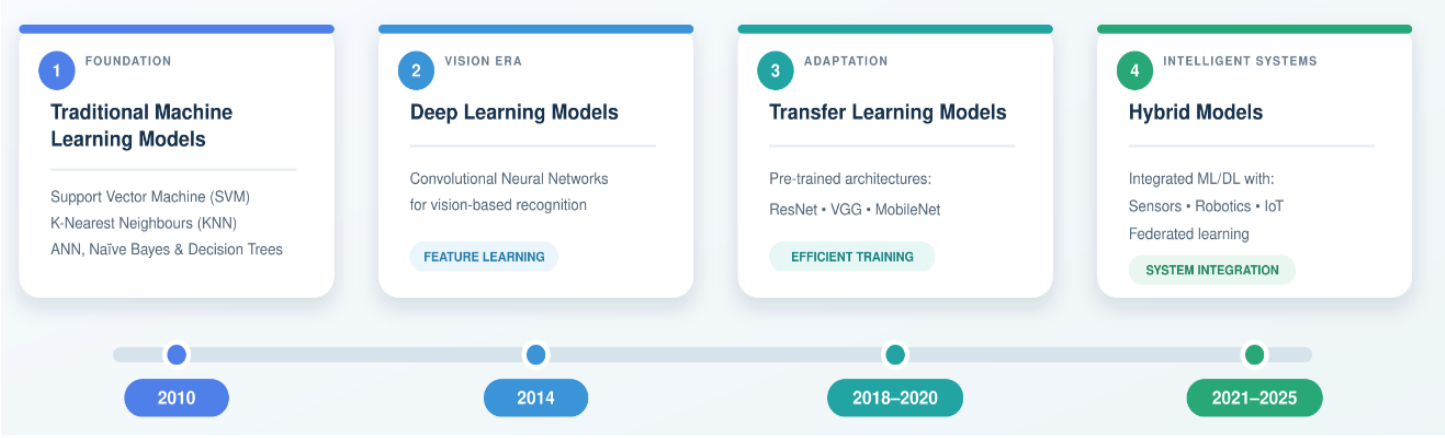


Figure 1 Evolution of computational methods used in automated waste-segregation systems (Fotovvatikhah et al., 2025)

As shown in Figure 1, technological development in automated waste segregation has gradually shifted from standalone classification algorithms towards intelligent and interconnected systems capable of supporting real-time identification, monitoring and physical sorting.

2.2 Common Issues in Existing Waste Classification and Sorting Systems

2.2.1 Dependence on Manual Segregation System

Manual segregation remains widely used because it requires lower initial investment and can accommodate a broad range of waste materials. However, the process is labor-intensive, time-consuming, and dependent on the judgement and consistency of individual workers. Waste handlers may also be exposed to contaminated materials, sharp objects, harmful substances, and biological hazards (Ahmad et al., 2025; Fotovvatikhah et al., 2025). As waste volume and diversity increase, maintaining consistent sorting quality becomes more difficult. These limitations have motivated the development of automated systems that reduce human involvement in direct waste handling.

2.2.2. Contamination and Visually Similar Materials

Waste materials are frequently contaminated, damaged, compressed, or partially covered by other objects. Such conditions can alter their visible color, shape, and texture, making accurate classification more difficult. Transparent plastic and glass, for example, may exhibit similar visual characteristics under an RGB camera, while paper and cardboard can be difficult to distinguish when their surface patterns are not clearly visible (Ahmad et al., 2025; Fotovvatikhah et al., 2025). Food residue, dirt, labels, and moisture can further change the appearance of an object. Therefore, high classification performance obtained using clean and individually positioned samples may not represent the model's performance in an actual mixed-waste environment.

2.2.3. Limited and Imbalanced Waste Datasets

The performance of an AI model is strongly influenced by the size, diversity, and quality of its training dataset. Many existing studies use datasets containing clean waste objects photographed against uniform backgrounds. These datasets may not sufficiently represent practical conditions such as shadows, cluttered backgrounds, overlapping objects, damaged packaging, and different camera angles (Fotovvatikhah et al., 2025). Dataset imbalance is another common issue, as frequently occurring waste classes may contain substantially more images than less common classes. A model trained using an imbalanced dataset may become biased towards the dominant categories and perform poorly for underrepresented materials.

Data augmentation techniques such as image rotation, horizontal flipping, scaling, cropping, and brightness adjustment can increase training diversity. However, augmentation cannot fully replace real images collected under different operating environments. Developing larger and more representative datasets is therefore necessary to improve model generalization in household, institutional, and industrial waste-management applications.

2.2.4. Environmental Variability

Lighting conditions, shadows, camera position, object orientation, and background complexity can significantly affect visual classification. A model trained under controlled illumination may experience reduced performance when deployed in an outdoor or semi-controlled environment (Ahmad et al., 2025; Fotovvatikhah et al., 2025; Vanitha et al., 2025). Reflective and transparent objects are particularly sensitive to illumination and viewing angles. Camera vibration and motion blur may also affect systems in which waste travels on a conveyor belt.

Image preprocessing methods can reduce some of these effects through resizing, normalization, noise filtering, and contrast adjustment. Nevertheless, excessive preprocessing may remove important visual features or increase processing time. A practical system must therefore balance image enhancement with the computational limitations of the embedded platform.

2.2.5. Computational Limitations of Embedded Devices

Deep learning models that perform well on desktop computers or GPU platforms may not operate at the same speed on low-cost embedded devices. Complex architectures generally require greater memory, processing power, and energy consumption, which can result in slow inference and delayed actuator response (Fotovvatikhah et al., 2025; Vanitha et al., 2025). This limitation is important because the sorting mechanism must respond before the waste item moves beyond the intended separation point.

Lightweight architectures such as MobileNetV2 provide a more suitable balance between classification performance and computational efficiency for Raspberry Pi deployment (Vanitha et al., 2025). Model optimization methods, including quantization, pruning, and conversion to TensorFlow Lite, can further reduce model size and inference time. However, optimization may introduce a trade-off between processing efficiency and classification performance. Therefore, models should be evaluated directly on the intended embedded hardware rather than relying only on results obtained from high-performance computing platforms.

2.2.6. Weak Integration between Classification and Mechanical Sorting

A high classification accuracy does not automatically produce an effective waste-sorting system. The image-capture process, classification output, object movement, and actuator response must be properly synchronized. Several studies primarily evaluate the software model without providing a detailed assessment of the physical sorting process (Fotovvatikhah et al., 2025; Mia et al., 2025). Delays in image acquisition or inference can cause the actuator to respond after the waste item has passed the sorting point.

Servo-controlled flaps provide a relatively simple and low-cost mechanism for small-scale systems, while conveyor belts can improve the continuity of material movement (Mia et al., 2025; Srinevasan et al., 2024). Robotic arms may provide greater flexibility but introduce additional mechanical complexity, control requirements, and energy consumption (Vanitha et al., 2025). The suitability of a sorting mechanism should therefore be assessed based on its load capacity, response time, positioning accuracy, reliability, and compatibility with the selected embedded controller

2.2.7. Cost, Scalability and Maintenance

Industrial waste-sorting systems may use advanced sensors, high-speed conveyors, robotic manipulators, and powerful computing hardware. Although such systems can offer high throughput, their cost and maintenance requirements may be unsuitable for households, educational institutions, and small organizations. Low-cost systems based on the Raspberry Pi, ESP32-CAM, standard cameras, and servo motors offer a more accessible alternative (Deebika et al., 2026; Mia et al., 2025; Srinevasan et al., 2024). However, these components may have limitations in processing speed, mechanical strength, durability, and long-term operation.

Scalability also remains a concern. A prototype that classifies one waste item at a time may not perform effectively when exposed to multiple or overlapping objects. Increasing the number of waste categories also increases classification complexity and may require a larger dataset, a more capable model, and a more advanced sorting mechanism. Consequently, cost reduction should not be achieved at the expense of system reliability and practical performance

METHODOLOGY

This study employed a structured narrative review to identify and compare current methods used in automated waste-classification and segregation systems. The review focused on studies involving sensor-based identification, machine learning, CNN-based image classification, lightweight neural networks, object detection, instance segmentation, multimodal sensor fusion, Edge AI processing, mechanical sorting and IoT-based monitoring. Attention was given to methods that could support low-cost, real-time and small-scale waste-segregation applications.

Relevant publications were identified primarily through Google Scholar, Scopus and IEEE Xplore. ResearchGate and individual journal or publisher websites were used as supplementary platforms to obtain or verify the full texts of relevant publications. The search covered studies published between 2018 and 2026, reflecting the period in which deep learning, embedded computing and Edge AI became increasingly prominent in automated waste-segregation research. The search used combinations of the following terms: "automated waste segregation", "waste classification", "smart waste sorting", "recyclable waste detection", "convolutional neural network", "object detection", "Edge AI", "embedded waste classification", "Raspberry Pi waste sorting", "ESP32 waste segregation", "sensor-based waste segregation" and "robotic waste sorting". The reference lists of relevant papers were also examined to identify additional studies. The criteria chosen for article selection are summarized in Table 1.

Table 1 Eligibility criteria used in the literature selection

Criteria	Inclusion	Exclusion
Publication Period	2017-2026	Published before 2017
Language	English	Other languages
Research focus	Automated waste recognition, classification or segregation	Collection routing, policy, landfill studies
Study type	Experimental, dataset-based or implemented study	Editorial, abstract or conceptual proposal
Technology	AI, computer vision, sensors, Edge AI mechanical sorting or IoT integration	No recognition or segregation component
Information availability	Sufficient method and performance information	Insufficient methodological details.

Following relevance screening and full-text assessment, 19 empirical studies were retained for the comparative analysis. These studies were selected because they reported experimental or implementation-based evidence for at least one component of an automated waste-segregation system. Three additional sources—a global waste-management reports, a systematic review and a foundational lightweight-CNN paper—were used to establish the background and analytical framework but were not included in the empirical frequency counts. The selected studies were categorized according to the technological methods employed. A single study could be assigned to more than one category when it incorporated multiple components, such as CNN classification, Edge AI processing and mechanical sorting. Therefore, the method frequencies presented in Figure 3 are not mutually exclusive.

Current automated waste-segregation systems employ a combination of sensing, artificial intelligence, embedded computing, and mechanical actuation rather than relying on a single classification technique. Sensor-based identification uses inductive, capacitive, moisture, ultrasonic, and weight sensors to distinguish waste according to measurable physical properties (Srinevasan et al., 2024). Camera-based methods apply CNNs and transfer learning to extract visual features and classify individual waste items, while lightweight architectures such as MobileNetV2 reduce computational requirements for embedded implementation (Ahmad et al., 2025; Deebika et al., 2026; Sandler et al., 2018). When multiple or overlapping objects are present, object-detection and instance-segmentation models provide both material classification and spatial localization (Alsubaei et al., 2022; Rajeev et al., 2025). Multimodal sensor fusion further improves decision reliability by combining visual predictions with physical measurements, particularly when materials have similar appearances or are contaminated . These methods can be implemented locally through Edge AI platforms using Raspberry Pi, OpenCV, and TensorFlow Lite to reduce network dependency and inference delay (Deebika et al., 2026; Mia et al., 2025; Sandler et al., 2018). The classification output is subsequently translated into physical separation through servo-controlled flaps, conveyor diverters, or vision-guided robotic manipulators (Paudel et al., 2024;

Zocco et al., 2025). IoT-based monitoring complements these methods by recording classification outcomes, monitoring bin capacity, and reporting operational faults (Vanitha et al., 2025). An overview of the current methods employed in automated waste-segregation systems and their respective functions is presented in Figure 2.

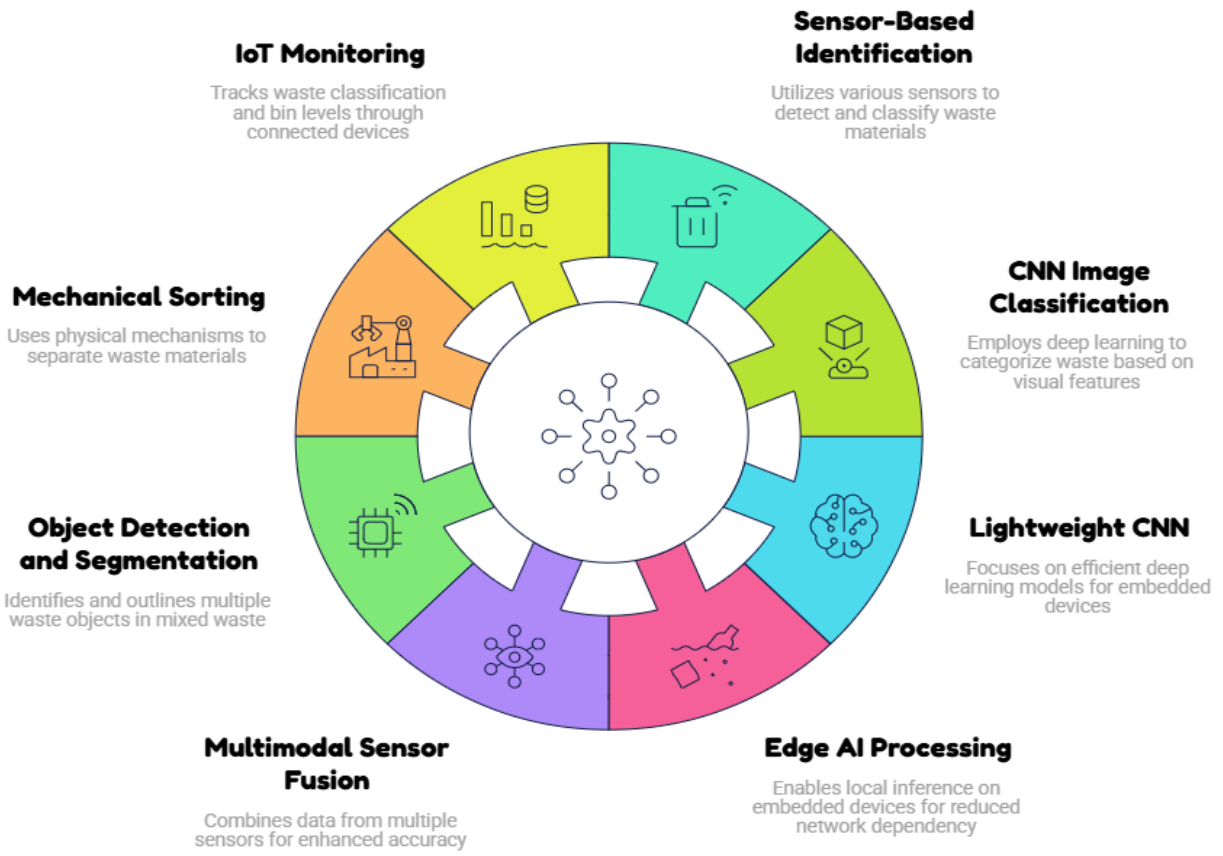


Figure 2 Approaches used in waste segregation system.

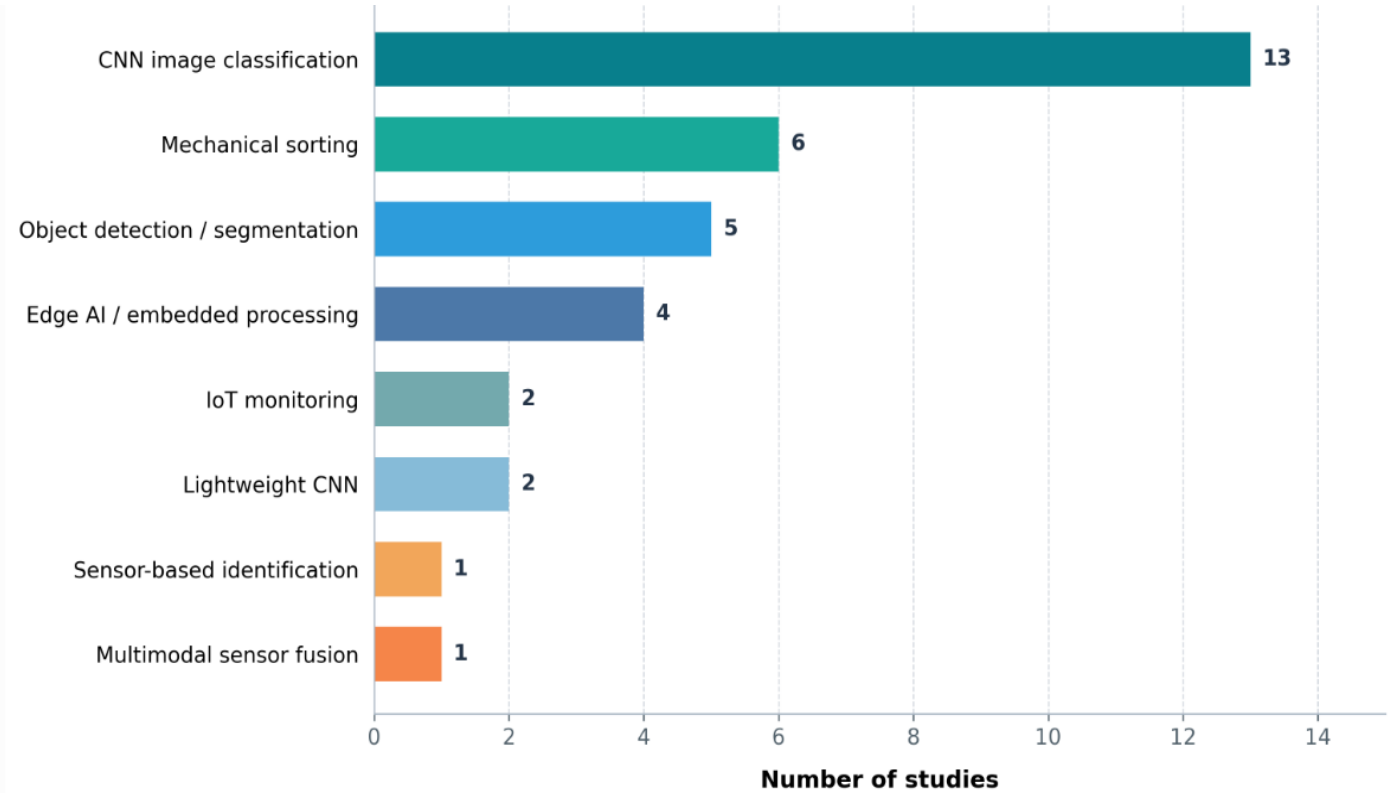


Figure 3 Frequency of methods identified across the 19 empirical waste-segregation studies.

Figure 3 summarizes the frequency of the principal methods identified across 19 empirical waste-segregation studies. CNN-based image classification was the most frequently reported approach, appearing in 13 studies, followed by mechanical sorting mechanisms in six studies and object detection or instance segmentation in five studies. Edge AI and embedded processing were identified in four studies, whereas lightweight CNN architecture and IoT-based monitoring were each explicitly examined in two studies. Sensor-based identification and multimodal sensor fusion received comparatively limited attention, with only one study identified for each method. These findings indicate that existing research predominantly focuses on improving visual classification performance, while fewer studies investigate sensor fusion and complete hardware-level integration. This imbalance highlights the need for future systems that combine visual intelligence with physical sensing, embedded processing and reliable mechanical segregation.

3.1 Sensor-based Identification

Sensor-based identification differentiates waste materials according to their measurable physical properties, such as moisture level, metallic content, weight, proximity, colour or material composition. In embedded waste-segregation systems, these sensors can provide input to a microcontroller that determines the appropriate waste category and activates the sorting mechanism. Srinevasan *et al.* for example, employed an ESP32-based supervised-learning mechanism for solid-waste segregation, demonstrating the potential of combining sensor inputs, embedded control and AI-based decision-making (Srinevasan et al., 2024). However, sensor-only systems may experience difficulty when different waste materials exhibit similar physical characteristics. Despite its potential to complement visual recognition, sensor-based identification remains less frequently investigated than camera-based classification in the reviewed studies.

3.2 CNN-Based Image Classification

Convolutional neural networks (CNNs) are the most employed method for automated waste recognition because they can automatically learn relevant visual features, including color, texture, shape and surface patterns. Ahmad et al. demonstrated the application of deep learning for intelligent waste sorting while highlighting the difficulties caused by contamination and variations in real-world waste appearance(Ahmad et al., 2025). Other studies have examined transfer learning and pretrained CNN models to reduce training requirements and improve classification performance. Vo et al. developed a deep-transfer-learning framework for trash classification, whereas Malik et al. evaluated multiple pretrained neural-network models for image-based waste recognition (Vo et al., 2019;Malik et al., 2022). Adedeji and Wang combined ResNet50 feature extraction with a support vector machine classifier, showing that CNN features can also be integrated with conventional machine-learning algorithms (Adedeji & Wang, 2019).

Researchers have additionally proposed specialized or modified CNN frameworks for waste-classification tasks. Bobulski and Kubanek applied deep learning to the classification of different plastic-waste categories, while Kaya compared architectures such as Xception and InceptionResNetV2 for a smart garbage-classification system (Bobulski & Kubanek, 2021; Kaya, 2023). Sayed et al. integrated deep learning with multi-objective beluga whale optimization to improve classification performance (Sayed et al., 2024). Islam et al. proposed an enhanced deep CNN framework, and Alalibo et al. compared modified convolutional architectures in terms of their effectiveness and computational efficiency (Alalibo et al., 2025; Islam et al., 2017). Collectively, these studies indicate that CNN-based classification is well established for recognizing images containing a dominant waste item. Nevertheless, classification models generally identify only the overall category of an image and may not determine the position or number of individual objects in mixed-waste scenes.

3.3 Lightweight CNN Architectures

Lightweight CNN architectures are designed to reduce model size, memory consumption and computational cost, making them more suitable for resource-constrained waste-segregation devices. MobileNetV2 uses inverted residual blocks and linear bottlenecks to achieve a balance between computational efficiency and recognition performance (Sandler et al., 2018). Deebika *et al.* applied MobileNetV2 on a Raspberry Pi for real-time waste classification, illustrating how a lightweight model can perform local inference without continuously depending on cloud computing(Deebika et al., 2026). Bircanoglu *et al.* similarly introduced RecycleNet (B.

Cenk et al., 2018) , an optimized CNN developed to classify recyclable objects with reduced model complexity. These methods are valuable for low-cost prototypes; however, reductions in model size must be carefully managed because excessive compression may decrease accuracy when waste objects are contaminated, partially visible or visually similar.

3.4 Object Detection and Instance Segmentation

Object-detection methods extend image classification by identifying both the category and location of each waste item within an image. This capability is particularly important when several objects appear simultaneously on a conveyor belt or when a robotic mechanism must determine the coordinates of an item. Rajeev *et al.* compared YOLOv5, YOLOv7 and YOLOv8 for e-waste detection, considering precision, recall, detection speed and training efficiency (Rajeev et al., 2025). Alsubaei *et al.* focused on small-object detection and classification within smart-city and IoT waste-management environments, addressing the challenge of recognizing waste that occupies only a limited area of an image (Alsubaei et al., 2022).

Instance-segmentation methods provide a more detailed output by estimating the pixel-level boundary of each detected object. Proença and Simões introduced the Trash Annotations in Context (TACO) dataset and evaluated Mask R-CNN for detecting and segmenting litter in complex real-world environments (Proença & Simões, 2020). Such approaches are better suited to overlapping, irregularly shaped or partially occluding waste than conventional image classification. However, object detection and instance segmentation generally require greater computational power and more detailed training annotations, which can restrict their use on low-cost embedded hardware.

3.5 Multimodal Sensor Fusion

Multimodal sensor fusion combines visual information with measurements from physical sensors to produce a more reliable waste-identification decision. For example, a camera may identify the apparent category of an object, while moisture, metal or weight sensors provide additional information about its material properties. This combination can reduce errors when different materials have similar colors or shapes. AI-enabled segregation platforms that integrate classification, embedded devices and physical sorting components illustrate the movement towards more comprehensive waste-management systems (Vanitha et al., 2025). Nevertheless, the reviewed literature contains substantially fewer studies on multimodal fusion than on image-based CNN classification (Fotovvatikhah et al., 2025). This represents an important research opportunity because many existing studies evaluate visual recognition independently without examining how camera data and physical sensor measurements should be combined under real operating conditions.

3.6 Edge AI and Embedded Processing

Edge AI refers to the execution of waste-recognition models directly on embedded devices, such as the ESP32, ESP32-CAM or Raspberry Pi. Local processing can reduce communication delays, lower dependence on internet connectivity and allow the sorting mechanism to respond immediately after an object is detected. Srinevasan et al. demonstrated an ESP32-based waste-segregation mechanism, whereas Deebika et al. used a Raspberry Pi with MobileNetV2 for real-time classification (Deebika et al., 2026; Srinevasan et al., 2024). WasteBelt further integrated a CNN, ESP32-CAM and conveyor automation to connect image acquisition, classification and mechanical sorting (Mia et al., 2025). These studies demonstrate the feasibility of low-cost embedded waste segregation, although memory capacity, processing speed, power consumption and model size remain significant limitations. Therefore, lightweight architectures and model-optimization techniques are particularly important for edge-based implementation (B. Cenk et al., 2018; Sandler et al., 2018).

3.7 Mechanical and Robotic Setting

A complete automated waste-segregation system must physically move each identified item into the appropriate container. Common mechanical solutions include servo-operated flaps, rotating platforms, conveyor diverters and robotic arms. Vanitha et al. incorporated automated segregation and robotic mechanisms into an AI-powered platform that also considered carbon-footprint tracking and waste trading (Vanitha et al., 2025). WasteBelt used

conveyor automation and an ESP32-CAM to coordinate visual classification with the physical movement of waste (Mia et al., 2025 . Paudel et al. integrated YOLOv8 detection with a Delta robotic arm and inverse kinematics, demonstrating how detected-object coordinates can be translated into robotic picking actions (Paudel et al., 2024).

Mechanical performance is affected not only by recognition accuracy but also by actuator response, conveyor speed, object spacing and communication delay. Zocco et al. examined synchronized object detection for autonomous sorting, mapping and material quantification, emphasizing the importance of coordinating detection results with the position and movement of waste objects (Zocco et al., 2025). Therefore, a model with high image-classification accuracy may still produce poor overall segregation performance if the mechanical system reacts too slowly or places objects in the wrong container.

3.8 IoT-based Monitoring and System Integration

IoT technology enables waste-segregation devices to transmit information such as bin-fill level, detected waste category, system status and collection requirements to a remote monitoring platform. Alsubaei et al. connected deep-learning-based waste detection with a smart-city and IoT environment (Alsubaei et al., 2022) , while Vanitha et al. presented an integrated platform combining waste segregation, carbon-footprint tracking and waste-trading functions (Vanitha et al., 2025). IoT connectivity can assist waste operators in monitoring equipment performance and planning collection schedules. However, network reliability, energy consumption, data security and system interoperability must be considered before such systems can be deployed at a larger scale.

3.9 Comparative Overview of the Methods

The methods identified in the reviewed studies differ in their operational principles, computational requirements and suitability for practical deployment. Table 2 compares the eight principal methods according to their approach, strengths, limitations and ideal application scenarios. This comparison provides a broader assessment than classification frequency alone because the most frequently reported method may not necessarily offer the most suitable solution for every waste-segregation environment.

Table 2 Comparative analysis of current methods used in automated waste-segregation systems

Method	Approach	Strength	Limitation	Ideal-Case use
Sensor-Based Identification	Uses inductive, capacitive, moisture, weight, proximity or ultrasonic sensors to distinguish waste according to its physical properties (Srinevasan et al., 2024).	Low computational requirement; rapid response; can operate without complex image processing; less affected by illumination.	Different materials may produce similar sensor readings; require calibration; performance may be affected by dirt, moisture and sensor positioning.	Low-cost systems that separate a small number of categories, particularly metal, wet and dry waste.
CNN Image Classification	Uses convolutional neural networks to classify waste images according to learned visual features such as colour, shape and texture (Ahmad et al., 2025)	High classification capability; automatically extracts image features; benefits from pretrained models and transfer learning.	Usually assigns one category to the entire image; sensitive to lighting, contamination and background variation; requires labelled training data.	Recognition of single or clearly positioned waste items on controlled conveyor lines or smart bins.
Lightweight CNN	Employs computationally efficient architectures, such as MobileNetV2 and RecycleNet, for	Smaller model size; faster inference; reduced memory and energy consumption; suitable for	Model compression may reduce accuracy; limited capacity for complex scenes; performance depends	Real-time classification using Raspberry Pi, ESP32-CAM or other resource-constrained edge devices.

	image classification on limited hardware (Deebika et al., 2026; Sandler et al., 2018)	embedded deployment.	on hardware optimization.	
Object Detection and Instance Segmentation	Uses models such as YOLO and Mask R-CNN to classify, locate or segment individual waste objects within an image(Proença & Simões, 2020)	Detects multiple objects simultaneously; provides object coordinates; handles cluttered scenes more effectively than image classification.	Requires detailed annotations and greater computational resources; may struggle with small, overlapping or partially hidden objects.	Conveyor-based sorting and robotic systems that must locate and collect individual waste items.
Multimodal Sensor Fusion	Combines camera-based recognition with data from moisture, metal, weight or proximity sensors to support the final classification decision (Fotovvatikhah et al., 2025; Vanitha et al., 2025).	Improves reliability by using complementary information; reduces dependence on visual appearance alone; distinguishes visually similar materials.	More complex hardware and data processing; requires sensor calibration, synchronization and an effective fusion strategy; increases system cost.	Mixed-waste environments where visual information alone is insufficient for reliable material identification.
Edge AI Processing	Executes trained AI models locally on embedded platforms such as Raspberry Pi or ESP32-CAM instead of relying on cloud processing (Mia et al., 2025)	Low response latency; can operate without continuous internet access; reduces data transmission and supports real-time control.	Limited processing power, memory and storage; complex models may operate slowly; require model optimization.	Standalone smart bins and real-time segregation systems installed in locations with limited network connectivity.
Mechanical and Robotic Sorting	Uses servo-controlled gates, conveyor diverters or robotic arms to move classified waste into designated containers (Paudel et al., 2024; Zocco et al., 2025)	Performs the actual physical separation; supports continuous operation; robotic mechanisms offer flexible object handling.	Vulnerable to mechanical wear, jamming and timing errors; performance depends on accurate synchronization with the recognition system.	Automated recycling lines and conveyor systems require continuous physical sorting of detected objects.
IoT-Based Monitoring	Connects waste-segregation devices to online platforms for remote monitoring, data transmission, bin-status reporting and collection management (Vanitha et al., 2025)	Enables real-time system monitoring; supports data logging, maintenance planning and optimized waste-collection schedules.	Depends on network availability; introduces cybersecurity, privacy and power-consumption concerns; does not independently perform segregation.	Distributed smart bins and smart-city waste-management systems requiring centralized monitoring and data analysis.

Quantitative evidence across the reviewed studies indicates that model performance was primarily reported using classification accuracy, precision, recall, F1-score or mean average precision (mAP), while operational indicators were less consistently documented. For example, the ResNet-based model evaluated by Ahmad et al. achieved a classification accuracy of 98.16% across 12 waste categories, demonstrating strong recognition performance under its experimental conditions (Ahmad et al., 2025). Other CNN, transfer-learning and object-detection studies also reported competitive predictive performance, although direct comparison is limited by differences in datasets, class distributions, waste categories and evaluation metrics. Classification accuracy should not be directly compared with the mAP values reported by object-detection and instance-segmentation models because these indicators represent different tasks. Lightweight architecture such as MobileNetV2 and

RecycleNet reduce model complexity and memory requirements, making them more suitable for resource-constrained platforms than larger CNN architectures (B. Cenk et al., 2018; Sandler et al., 2018). Embedded implementations using Raspberry Pi and ESP32-based platforms further demonstrate the feasibility of performing local inference near the sorting mechanism (Deebika et al., 2026; Mia et al., 2025; Srinevasan et al., 2024). However, inference latency, processor and memory utilization, energy consumption and sorting throughput were either inconsistently reported or unavailable in several reviewed studies. Consequently, the available literature supports lightweight CNNs and Edge AI as practical solutions because of their balance between recognition performance and computational efficiency, rather than establishing them as universally superior based on accuracy alone. Future studies should report device-level latency, power consumption, correct-bin rate and items sorted per minute together with conventional recognition metrics to enable more reliable end-to-end comparison.

Overall, no single method fully satisfies the identification, processing, monitoring and physical-sorting requirements of an automated waste-segregation system. CNN-based classification remains the most widely studied approach, but its practical effectiveness can be improved through sensor fusion, edge processing and reliable mechanical sorting. Therefore, an integrated system that combines complementary methods is generally more suitable for real-world deployment, although improvements in accuracy must be balanced against hardware complexity, processing requirements and implementation cost.

RESULTS AND DISCUSSION

Recent technological advancements have significantly simplified waste segregation by reducing dependence on manual identification and enabling faster, more consistent and increasingly automated sorting processes. The progression from conventional sensors and machine-learning algorithms to deep-learning models, edge computing, object detection and robotic mechanisms has allowed waste items to be recognized, located and physically separated with less human intervention (Fotovvatikhah et al., 2025; Mia et al., 2025; Rajeev et al., 2025). These developments have also supported real-time operation and the integration of monitoring functions within smart waste-management systems (Alsubaei et al., 2022; Vanitha et al., 2025). Nevertheless, the benefits achieved vary according to the waste characteristics, operating environment, computing platform and level of system integration. Therefore, this section synthesizes the findings of the reviewed studies based on four key outcomes as shown in Figure 4 which covers on waste recognition, identification and localization of individual objects, suitability for real-time deployment, and successful physical separation. As the reviewed studies employed different datasets, waste categories, hardware platforms and evaluation metrics, their reported results are interpreted according to their respective applications rather than treated as a direct performance ranking.

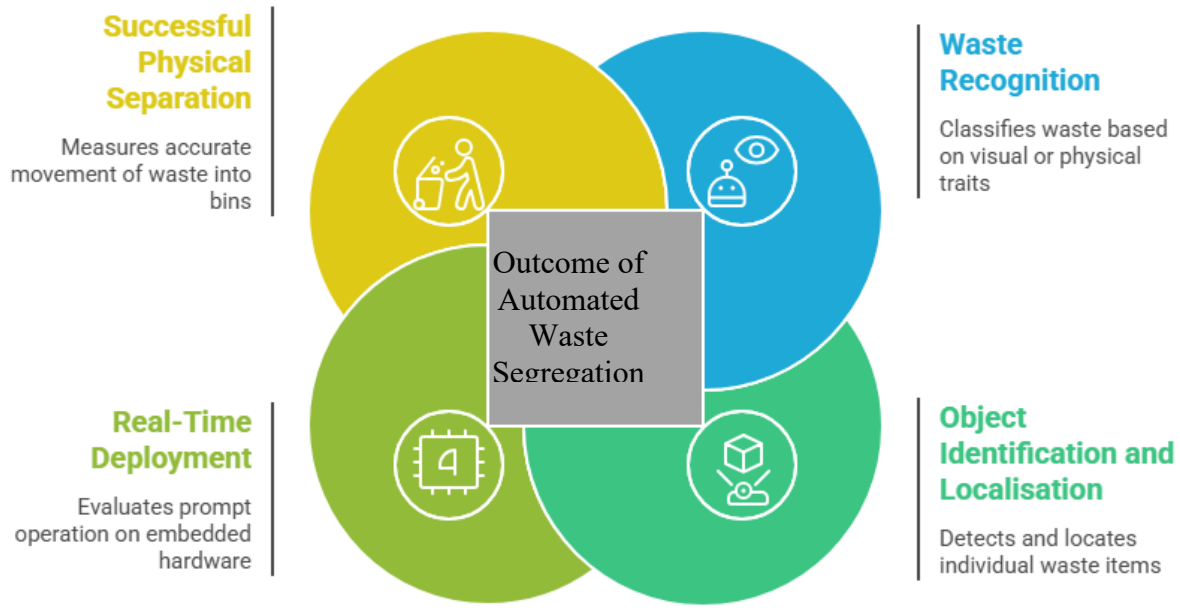


Figure 4 Summary of the principal implementation outcomes identified in the reviewed studies.

4.1 Image-Based Waste Recognition

CNN-based image classification was the most frequently identified approach in the reviewed empirical studies, appearing in 13 of the 19 studies represented in Figure 3. Studies using transfer learning, pretrained networks and modified CNN architecture demonstrate the value of learned visual features for distinguishing waste categories (Ahmad et al., 2025). For example, the enhanced CNN framework proposed by Islam et al. was evaluated across multiple waste datasets, illustrating the potential of more advanced feature extraction for image classification (Islam et al., 2017). These findings suggest that CNN classification is a suitable choice when an image contains one clearly presented waste item. Its usefulness for physical segregation is more limited when several items appear together, because an image-level prediction does not specify which object should be collected.

4.2 Identification of Individual Waste Objects

Object detection produces a more useful output when the system must handle multiple items or guide a sorting mechanism. Rajeev et al. compared YOLOv5, YOLOv7 and YOLOv8 for seven categories of electronic waste and reported that YOLOv8 performed best within their experimental setting (Rajeev et al., 2025). However, that result should not be generalized to every waste dataset or computing platform. Instance segmentation offers further detail by outlining individual objects. The TACO study demonstrated promising Mask R-CNN results for litter in complex scenes (Proença & Simões, 2020), while also reporting that more annotated images were needed before reliable deployment. Taken together, these studies indicate that detection or segmentation is better suited than whole-image classification when object location is necessary, although the added annotation and processing requirements must be considered.

4.3 Real-Time and Embedded Implementation

The practical outcome of a recognition model also depends on whether it can operate on the intended device. Raspberry Pi and ESP32-based systems illustrate the feasibility of performing classification near the point of collection (Deebika et al., 2026; Mia et al., 2025; Srinevasan et al., 2024). Lightweight architectures such as MobileNetV2 (Sandler et al., 2018) and RecycleNet (B. Cenk et al., 2018) address this requirement by reducing computational demands. The best outcome in this setting is therefore a balance between recognition performance and response time, rather than classification accuracy alone. A larger model may perform well during offline testing but may be unsuitable if its inference time delays a conveyor or actuator. Studies involving embedded devices consequently need to report device-level measurements, including inference time, memory use and power consumption, alongside classification metrics.

Nevertheless, the quantitative evidence remains incomplete because several embedded implementations did not simultaneously report inference latency, memory utilization, power consumption and sorting throughput. The suitability of lightweight CNNs and Edge AI platforms should therefore be interpreted as a practical balance between predictive performance and computational requirements rather than as a definitive performance ranking.

4.4 From Recognition to Successful Segregation

Correctly recognizing waste is only one stage of successful segregation. Systems that combine computer vision with conveyors or robotic arms demonstrate how a prediction can be translated into physical sorting (Mia et al., 2025; Paudel et al., 2024). Work on synchronized detection further highlights the importance of coordinating object location, conveyor movement and the sorting action (Zocco et al., 2025). For a complete system, the most meaningful outcome is the proportion of items placed in the correct container, together with its sorting rate and error rate. Sensor-based identification can provide information about material properties (Srinevasan et al., 2024) , while combining sensors with vision may help resolve visually ambiguous items; however, the reviewed references provide insufficient comparable evidence to conclude that multimodal fusion consistently produces the highest segregation accuracy. IoT functions support monitoring and reporting (Alsubaei et al., 2022; Vanitha et al., 2025), but they should be evaluated separately from the accuracy of physical sorting.

Overall, the strongest method depends on the task being measured. CNNs are well supported for classifying clearly presented waste images, object detection is more suitable when items must be located, and lightweight models are useful when decisions must be made on limited hardware. For an operational segregation system, the most promising configuration combines reliable identification with timely mechanical action. The present literature does not establish a single universally best method, because few studies evaluate all these components under the same real-world conditions. Future comparisons should use shared waste categories and report both recognition metrics and end-to-end sorting outcomes.

The qualitative suitability assessment in Figure 5 was developed by mapping the primary and supporting functions of each method against five operational outcomes: single-item recognition, multi-item identification and localization, on-device processing, physical sorting and remote monitoring. The assessment was based on the functional capabilities and implementation evidence reported in the 19 empirical studies rather than on a numerical performance score. A method was rated as Direct when it independently produced the corresponding outcome as one of its primary functions. It was rated as Support when it contributed to or improved the outcome but could not perform the function independently. A dash (–) indicates that the method had no substantial functional contribution to the outcome or that sufficient supporting evidence was not identified in the reviewed studies. Therefore, the matrix represents a functional suitability assessment and should not be interpreted as a statistical ranking of performance.

	Single-item recognition	Multi-item localisation	On-device processing	Physical sorting	Remote monitoring
Sensor-based identification	DIRECT	–	SUPPORT	SUPPORT	–
CNN image classification	DIRECT	–	SUPPORT	SUPPORT	–
Lightweight CNN	DIRECT	–	DIRECT	SUPPORT	–
Object detection / segmentation	SUPPORT	DIRECT	SUPPORT	SUPPORT	–
Multimodal sensor fusion	DIRECT	SUPPORT	SUPPORT	SUPPORT	–
Edge AI processing	SUPPORT	SUPPORT	DIRECT	SUPPORT	SUPPORT
Mechanical / robotic sorting	–	–	SUPPORT	DIRECT	–
IoT monitoring	–	–	SUPPORT	–	DIRECT

Figure 5. Qualitative functional suitability of automated waste-segregation methods across five operational outcomes based on evidence from the reviewed studies.

The qualitative suitability matrix shown in Figure 5 indicates that no individual method provides the best outcome across all functions of an automated waste-segregation system. CNN image classification and sensor-based identification are most suitable for recognizing clearly presented waste items, while multimodal sensor fusion offers a potentially more reliable outcome when visual information alone cannot distinguish materials with similar appearances (Adedeji & Wang, 2019; Ahmad et al., 2025; Srinevasan et al., 2024). For mixed-waste environments, object detection and instance segmentation provide the strongest outcome because they can identify and locate multiple items simultaneously, making their outputs more useful for automated handling and robotic sorting (Alsubaei et al., 2022; Proença & Simões, 2020; Rajeev et al., 2025). Lightweight CNN architectures and edge AI processing are preferable for real-time deployment on embedded hardware because they reduce inference time and computational demand, although this efficiency may involve a trade-off in recognition performance. Mechanical and robotic sorting provides the most direct outcome for physical segregation because it converts the recognition decision into an actual sorting action, whereas IoT monitoring contributes mainly to remote supervision, data collection and operational management (Alsubaei et al., 2022;

Vanitha et al., 2025). Therefore, the literature suggests that the strongest overall solution is an integrated configuration that combines object detection or multimodal recognition with optimized edge processing and a synchronized mechanical sorting mechanism. Its effectiveness should be assessed using both algorithmic metrics, such as accuracy, precision, recall and detection performance, and operational outcomes, including inference time, correct-bin rate, sorting throughput and system reliability.

4.5 Research Gaps and Deployment Challenges

Despite the promising results reported in the reviewed studies, three important research gaps limit the transition from experimental waste recognition to reliable real-world segregation. First, many models were evaluated using clean, individually positioned images or controlled backgrounds, whereas operational waste streams contain contaminated, damaged, overlapping and irregularly oriented objects. Consequently, high classification accuracy under laboratory conditions may not represent performance under changing illumination, motion blur, occlusion and material contamination (Ahmad et al., 2025; Fotovvatikhah et al., 2025; Proença & Simões, 2020). Second, multimodal sensor fusion remains insufficiently investigated. Although combining visual classification with metal, moisture, weight or proximity sensing could improve the recognition of visually similar materials, the reviewed studies provide limited evidence regarding fusion strategies, sensor calibration, processing delay and the resulting improvement in end-to-end segregation accuracy (Srinevasan et al., 2024; Vanitha et al., 2025). Third, synchronization between classification algorithms and mechanical sorting mechanisms remains a critical but underreported challenge. A correct prediction may still result in incorrect physical separation when inference delay, conveyor speed, object spacing and actuator response are not coordinated. Existing conveyor- and robotic-based studies demonstrate the feasibility of integrated sorting, but relatively few evaluate correct-bin rate, sorting throughput, actuator failure, material jamming and long-term mechanical reliability under continuous operation (Mia et al., 2025; Paudel et al., 2024; Zocco et al., 2025). These gaps indicate that future studies should move beyond standalone algorithmic accuracy and evaluate complete systems using realistic waste samples and combined computational, sensing and mechanical performance indicators.

CONCLUSION

This review examined the principal methods used in automated waste-segregation systems, including sensor-based identification, CNN image classification, lightweight CNN architectures, object detection and instance segmentation, multimodal sensor fusion, edge AI processing, mechanical sorting and IoT-based monitoring. The findings show that CNN-based image classification remains the most frequently studied method and is effective for recognising clearly presented waste items. Object detection and instance segmentation provide better outcomes when multiple items must be identified and located, whereas lightweight CNNs and edge AI are more suitable for real-time implementation on resource-constrained devices. Mechanical and robotic mechanisms are essential for translating recognition results into physical separation, while IoT technologies support remote monitoring and operational management. Therefore, no single method can independently fulfil all the requirements of a complete waste-segregation system.

Overall, the most promising approach is an integrated system that combines reliable visual recognition or multimodal sensing with efficient edge processing and a synchronised mechanical sorting mechanism. However, the reviewed studies commonly use different datasets, waste categories, hardware platforms and evaluation metrics, making direct performance comparisons difficult. Future research should evaluate complete systems under realistic conditions involving mixed, contaminated, overlapping and irregularly positioned waste. Standardised datasets and evaluation measures should also be adopted to assess recognition accuracy, inference time, correct-bin rate, sorting throughput, energy consumption and long-term mechanical reliability. Addressing these areas will support the development of waste-segregation systems that are more accurate, practical and suitable for large-scale deployment.

5.1 Future Work: Proposed Edge AI-Powered Waste-Sorting Prototype

Future work will focus on developing an integrated Edge AI waste-sorting system that addresses several limitations identified in the reviewed literature, particularly the lack of locally representative datasets and

complete end-to-end system evaluation. The proposed system will identify and categorise common recyclable materials, including plastic, metal and paper, using a lightweight Convolutional Neural Network trained in Edge Impulse with images of waste collected under Malaysian conditions. The trained model will be deployed on a resource-constrained microcontroller to perform local and real-time inference, allowing the system to operate with minimal dependence on cloud connectivity. Based on the predicted waste category, the microcontroller will activate a servo-controlled mechanism to direct each item into the appropriate collection bin.

In addition to automated sorting, the proposed system will incorporate a Lifecycle Assessment dashboard to estimate the environmental benefit of diverting recyclable materials from landfills. The dashboard will combine the identified material category with appropriate emission factors to calculate the estimated kilograms of carbon dioxide equivalent avoided for each item or quantity of material recovered. The expected outcome is a functional and low-cost prototype that integrates waste recognition, edge processing, physical separation and environmental-impact monitoring within a single platform. Its performance will be evaluated using classification accuracy, precision, recall, F1-score, inference time, correct-bin rate and sorting throughput, while the carbon estimates will be reported with clearly defined system boundaries and data sources. The conceptual design of the proposed system is illustrated in Figure 6, integrating Edge AI classification, automated physical separation and real-time environmental-impact estimation within a single low-cost platform.

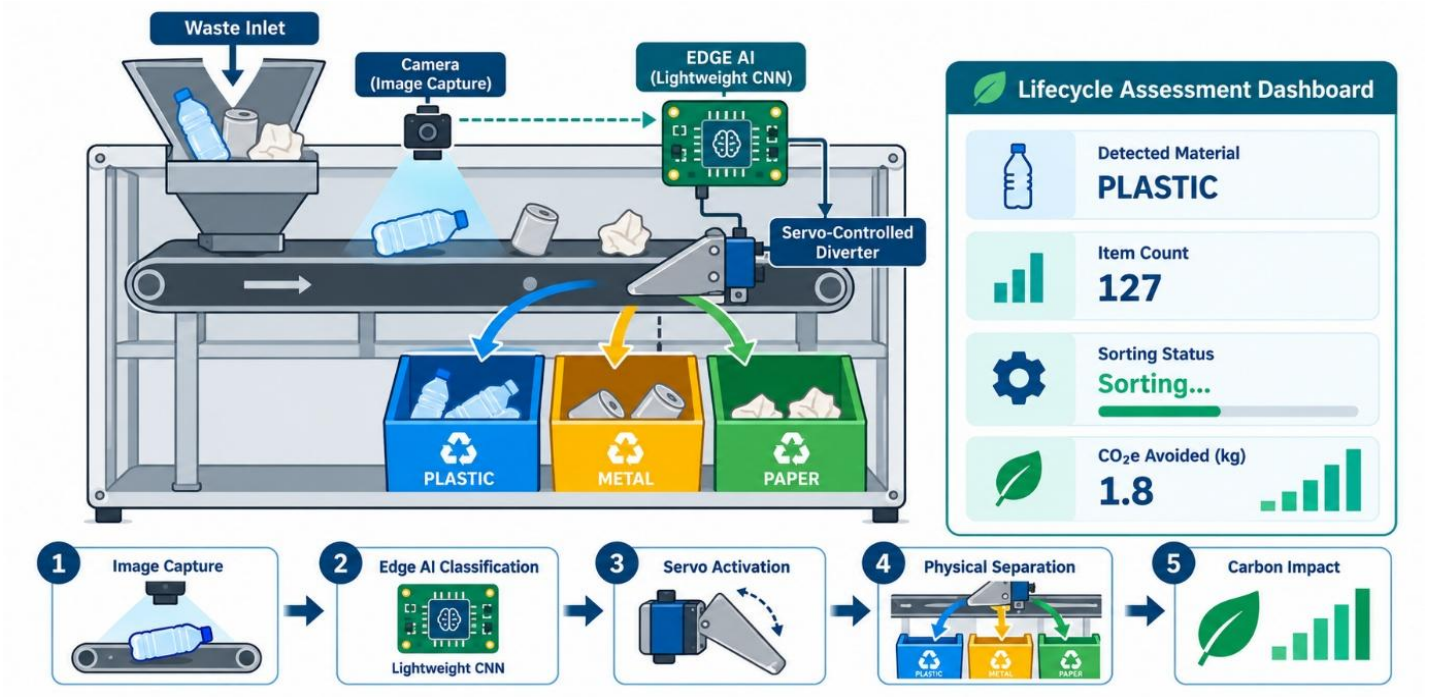


Figure 6 Conceptual design of the proposed Edge AI-powered waste-sorting prototype incorporating real-time material classification, servo-controlled physical separation and carbon-impact monitoring.

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