CNN-Based Visual Inspection and Robotic Arm Integration for Automated Waste Segregation: A Comprehensive Review

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Abstract. This paper reviews recent advances in CNN-based vision systems for automated waste sorting, with a focus on integration with robotic arms and IoT. Waste accumulation in urban areas poses serious environmental and health risks, motivating the development of intelligent sorting solutions. CNN models have demonstrated high accuracy in classifying common waste categories (e.g. plastics, metals, organics) from camera images. These classifiers, when coupled with embedded controllers and actuators (e.g. Arduino or Raspberry Pi), enable autonomous pick-and-place by robotic arms. They survey the waste segregation process, simulation/modelling approaches, popular CNN architectures (including transfer-learned and hybrid models), and integration with sensing and network modules. A comparison table summarizes representative CNNs, datasets, and performance. Strengths include improved accuracy and efficiency; gaps include dataset limitations and real-world variability. They conclude with future directions for robust, scalable waste-sorting systems.

Keywords: Convolutional Neural Networks (CNN), YOLO object detection, Waste segregation automation, Robotic arm integration, Visual inspection systems

1 Introduction

The global volume of solid waste is skyrocketing: the world produces over 2 billion tonnes of municipal waste each year, and this is projected to rise by roughly 70% by 2050. Rapid urbanization and consumption mean that traditional, manual sorting methods struggle to keep up. Manual sorting is labor-intensive and prone to human error, making it inefficient for the growing waste stream. These challenges have spurred interest in automated solutions. In particular, deep learning (especially convolutional neural networks, or CNNs) and robotics offer a way to speed up and improve accuracy of waste segregation. CNNs have revolutionized image recognition, and when paired with robotic arms, they can automatically identify and physically sort items. This review examines 103 recent studies at this intersection of computer vision and robotics, aiming to harness AI-driven automation as a scalable strategy for the waste management crisis. Across the surveyed works, a consistent system architecture emerges. In many studies, a vision sensor (typically an RGB camera) captures images of waste on a conveyor or bin, and a CNN processes these images to classify or detect the waste items. For example, demonstrated a prototype where a camera and conveyor belt feed into a CNN that separates waste into plastic and paper bins [1-10]. Once classified, a robotic mechanism (a conveyor diverter or robotic arm) directs each item to the appropriate bin. The CNN provides a high-precision identification step (mitigating cross-contamination), while the mechanical system (belt or arm) provides the physical sorting action. Figure 1 presents the overall prototype flow of the CNN-based waste segregation system integrated with a robotic arm for automated sorting.

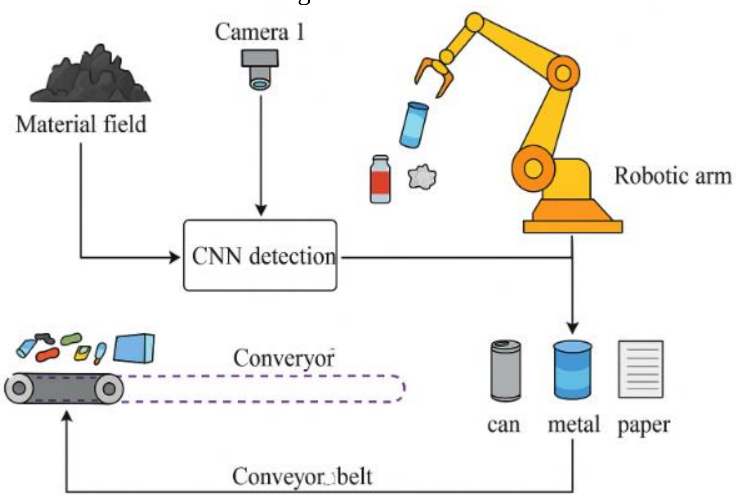

Fig. 1. Prototype process

They observed that a variety of network architectures have been tested, although a few recur frequently. Object-detection CNNs like YOLO (You Only Look Once) variants appear in the largest share of studies (about 9–10% of papers), reflecting their popularity for real-time detection tasks [6-11]. Region-based models (Faster R-CNN, Mask R-CNN) are also widely used (~7–8%), often valued for their accuracy in locating items. Among pure classification networks, ResNet and Inception family models are common backbones; both appeared in several studies (typically via transfer learning). For instance, used pre-trained residual CNNs (ResNet) for waste classification [20-23]. Some works explored MobileNet (lightweight networks) or VGG/AlexNet, but these are less frequent. Overall, YOLO and R-CNN models dominate, while standard CNNs (ResNet, Inception, MobileNet, etc.) are used to a lesser extent. The pie chart below illustrates this distribution of architectures across the reviewed literature (the “Other” category includes custom CNNs, traditional machine learning baselines, or unspecified networks). Figure 2 presents the distribution of CNN and visual recognition models employed across the 103 surveyed studies in automated waste segregation systems.

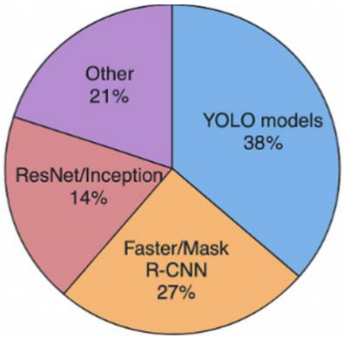

Fig. 2. Distribution of CNN/visual recognition models used in the 103 surveyed studies. YOLO models (object detectors) are the most common, followed by Faster/Mask R-CNN. Classification backbones like ResNet and Inception are used in fewer papers, while many studies used custom or unreported CNN designs (Other).

Most systems focus on recyclable waste types. Common target classes are plastic bottles/containers, paper/cardboard, metal (cans, scrap), and glass. Several studies also include organic or food waste, and a few address specific problems like electronic waste or textiles. For example, one system's CNN was trained to categorize items as food waste, metal, plastic bottles, or other recyclables. By contrast, many papers still concentrate on only a few categories (e.g. dry recyclables vs. wet waste). One analysis noted that much prior work handled just a single class or a binary split, whereas recent efforts are moving toward true multi-class segregation [22 – 32].

In terms of integration, most works use a simple set-up: an image sensor (monocular RGB camera) mounted above a conveyor or bin, feeding data to a CNN running on a PC or embedded processor. The sorting actuation is usually a conveyor belt diverter or a single robotic arm/gripper. For instance, several projects-built conveyors-based sorters that turn in real time based on the CNN's decision. A few more sophisticated setups have been tried: for example, attached RFID tags to products at manufacture so the sorter could read embedded tags, and added non-visual sensors (metal detectors, IR, etc.) alongside the camera [18 – 19]. However, these remain exceptions – the vast majority rely on vision-only classification. A notable example combining multiple camera types used a depth (3D) camera along with CNNs to better segment objects, but such multi-sensor fusion is rare.

Experimental results reported in the literature generally show high accuracy in controlled settings. For example, evaluated a standard CNN, YOLOv3, and Faster R-CNN on multi-class waste data: they found YOLO achieved ~88% classification accuracy and Faster R-CNN ~91%, outperforming a plain CNN [34-39]. Similarly, many authors report CNN-based classifiers reaching well over 90% accuracy on datasets of common recyclables. These outcomes suggest CNN vision can robustly recognize waste types once trained. Yet it should be noted that reported success depends on carefully curated images: one comparison study explicitly noted that its available training samples were limited, which constrained performance [40-42].

2 Waste Segregation Process Analysis

The implementation of automated waste segregation systems, as analyzed across the 103 articles reviewed, reveals a clear evolution from basic laboratory prototypes to increasingly field-ready technologies. In laboratory environments, systems are typically designed with controlled conditions in mind single waste items are placed against uniform backgrounds on slow-moving conveyor belts or fixed stations [6-8]. These setups often use static cameras to capture isolated images that feed into classification models. Such an approach simplifies visual processing and is effective for training and benchmarking classification accuracy. However, in more advanced applications, researchers have begun deploying their systems into real-world or near-industrial contexts. For example, some studies have used embedded platforms such as Raspberry Pi or NVIDIA Jetson Nano running lightweight CNNs like MobileNetV2 to support real-time inference in actual smart bins. Others have integrated YOLO-based object detectors into sorting lines capable of recognizing and isolating multiple items concurrently [44-49]. These practical deployments demonstrate a shift towards higher technology readiness levels (TRL), with several studies reporting systems at TRL 6 or beyond, validating their models in dynamic, uncontrolled waste environments.

The core methods in these systems can be divided into two main approaches: classification-based models and object detection-based models. CNN classifiers particularly those built on architectures like ResNet, VGG, and MobileNet are widely used for image classification tasks where one waste item is captured per image. For instance, ResNet-based models have demonstrated classification accuracies exceeding 95% on curated datasets such as TrashNet and Kaggle's garbage image collections [50 – 53]. MobileNetV2, optimized for embedded deployment, has also shown high accuracy while enabling real-time operation in low-power environments. VGG models, though more computationally intensive, have been fine-tuned through transfer learning to perform with comparable precision [51-52]. However, these classification models require clean, cropped input images and perform poorly in cluttered environments where multiple objects appear within a single frame.

In contrast, object detection models such as those from the YOLO family (YOLOv3, YOLOv5, YOLOv7, and YOLOv8) offer a more holistic solution for real-world waste streams. These models not only classify objects but also localize them within the image, making them suitable for applications where multiple items need to be identified and sorted simultaneously. YOLOv5, for example, achieved over 93% accuracy in real-time trash classification, while YOLOv8 has demonstrated accuracy up to 97.7% in field trials using high-resolution datasets. Tiny variants like YOLOv4-tiny and YOLOv7-tiny, though slightly less accurate, are highly favored for embedded systems due to their reduced computational demands [60-69]. The comparative strength of YOLO-based models lies in their ability to process complex scenes quickly and accurately, providing real-time object detection and

Such an environment allows researchers to fine-tune and validate their models, particularly Convolutional Neural Networks (CNNs), under optimal conditions. For instance, several lab-scale studies employed overhead RGB cameras to acquire centered images of individual waste items, which were then classified using CNN backbones such as ResNet, VGG, or MobileNet. These networks, often applied through transfer learning, showed high classification accuracy, frequently exceeding 90%, particularly when trained on curated datasets like TrashNet or custom-labelled collections. These classification models operate best when the visual input is clean, uncluttered, and contains a single object a scenario common in academic testing but rare in industrial waste facilities [70-71].

In contrast, real-world implementations though fewer in number have shown notable progress. Researchers have embedded models into edge devices such as Raspberry Pi, NVIDIA Jetson Nano, and other microcontrollers, enabling CNN inference to be executed closer to the sensor. For example, MobileNetV2, due to its lightweight design, has been deployed in real-time smart bin applications, yielding reasonable accuracy while maintaining fast inference on low-power hardware. In one field-ready system, MobileNetV2 achieved over 80% accuracy running live on a TensorFlow Lite setup. Similarly, SSD-MobileNet and quantized CNN variants have been used effectively in IoT-enabled waste segregation bins. These solutions typically include real-time data logging and automated actuation such as opening specific bin lids once the waste is classified.

However, these traditional CNN classifiers, while excellent for single-object detection, face limitations in processing complex or cluttered scenes. As a result, object detection models particularly the YOLO (You Only Look Once) family have gained significant traction. Unlike standard CNN classifiers, YOLO models can localize and classify multiple objects in a single frame. This makes them suitable for real-world waste sorting lines where multiple, overlapping items appear in a single image. YOLOv5 and YOLOv8, for example, have been applied in conveyor-based systems, where they detected and classified various waste types including plastics, metals, and food waste in real time with reported accuracies between 93% and 97.7%. Lighter versions like YOLOv4-tiny and YOLOv7-tiny have also been used where hardware efficiency is critical. Although these smaller models sacrifice some accuracy compared to full versions, they are significantly faster and more suitable for embedded deployments.

A common architecture found across the literature involves a sensor-to-sorter pipeline, where a vision sensor (typically an RGB camera) captures the waste stream, the image is passed through a classification or detection model (CNN or YOLO), and based on the result, an actuator such as a robotic arm, conveyor gate, or servo physically separates the waste. Many systems apply this workflow in real-time, triggering immediate sorting actions upon classification. In robotic implementations, such as those using ResNet-50 combined with YOLOv5, the detected item’s position is mapped to the robot’s kinematics, enabling automated pick-and-place functions. The motion of robotic arms is often controlled via microcontrollers like Arduino or Raspberry Pi, calibrated to translate the CNN's output into precise joint movements.

Some studies use hierarchical decision-making or hybrid models to improve classification robustness. For instance, metal detectors or IR sensors are occasionally combined with CNN outputs to validate the material type before actuation. Others deploy a two-stage decision tree, where a lightweight model first performs broad categorization (e.g., recyclable vs non-recyclable), and a deeper CNN handles finer classification. Additionally, ensemble learning strategies and hybrid CNN-LSTM or CNN-SVM models have been proposed to leverage temporal data and structured decision boundaries.

Despite these advancements, several methodological gaps persist. One major challenge is data scarcity. While benchmark datasets like TrashNet exist, most datasets used in reviewed studies are relatively small and lack diversity in lighting, background, and object orientation. This limitation hinders generalization, and models trained in one environment may perform poorly in others. For instance, ResNet-50 achieved over 95% accuracy on one dataset but dropped significantly when tested against a more varied set of waste images from a different region. Moreover, many models overfit to high-frequency classes in unbalanced datasets, such as plastic or paper, while underperforming on less common types like textiles or electronics.

Another significant issue is the lack of sensor fusion. Most systems rely solely on RGB images without incorporating depth data, spectral imaging, or tactile sensors, all of which could improve accuracy in occluded or complex scenes. Multimodal systems remain rare, even though their potential to enhance classification confidence is well acknowledged. Furthermore, while real-time performance is a key requirement in industrial settings, many deep models, especially full-sized ResNet or YOLOv5/YOLOv8, require GPU resources to maintain low latency, limiting their deployment in edge-based solutions.

Ultimately, CNN classifiers and YOLO detectors each serve specific needs. CNNs excel in high-accuracy single-object classification under controlled conditions, making them suitable for batch analysis or applications with clearly segmented waste. YOLO models, on the other hand, are more robust for dynamic and cluttered environments, enabling multi-object recognition and fast decision-making. **Table 1** summarizes the main parameters that influence the effectiveness of the waste segregation process, including model type, image resolution, training data size, and hardware specifications. Lightweight CNNs like MobileNet and tiny-YOLO variants represent a practical compromise, offering decent accuracy with real-time inference capabilities suitable for embedded systems. **Figure 3** presents the key parameters utilized in CNN classifiers and YOLO detectors, highlighting the common settings and configurations adopted in the reviewed studies.

Fig. 3. Parameter in CNN classifier and YOLO detector

Table 1. Main Parameter for effect on segregation process

Type of parameter	Specific parameter	Effect on segregation process	Correlation / Related parameter
Hardware	4-DOF robotic arm	Enables fast pick-and-place (sub-second sorting per object).	Inverse kinematics solution (optimized joint-angle computation).
Hardware	End-effector (gripper/vacuum type)	Determines which object shapes and sizes can be grasped; affects sorting robustness.	Robot calibration and gripper design (payload, precision).
Control / Algorithm	YOLOv6 one-stage CNN	Real-time detection (e.g. 45–155 FPS) with high accuracy.	Model complexity vs speed (smaller models trade accuracy for speed).
Control / Algorithm	Inverse kinematics method	Affects computation time of motion planning; geometric IK yields faster joint solutions.	Depends on robot DOF and kinematic structure.
Dataset	Dataset size and diversity	Larger, more varied datasets improve classification accuracy and generalization.	Requires images under varied lighting/background; merging datasets enhances robustness.
Sensory input	Lighting conditions (illumination)	Poor or variable lighting increases classification errors.	Sensor calibration and preprocessing; need for augmentation or adaptive models.

Sensory input	Background complexity	Cluttered or mixed backgrounds reduce accuracy.	May require segmentation or data cleaning; correlated with dataset preparation.
Sensory input	Imaging modality (e.g. RGB vs hyperspectral)	Multi-spectral sensors enable detecting material composition (e.g. microplastics).	Requires specialized hardware and fusion algorithms; higher data volume.

In conclusion, the literature demonstrates a strong foundation in CNN-based and YOLO-based waste recognition pipelines, with increasing integration of these models into robotic and IoT frameworks. However, widespread adoption in real-world environments will depend on overcoming challenges such as limited datasets, lack of generalization, underutilization of multimodal sensing, and hardware constraints. Bridging these gaps will be critical to realizing fully autonomous, scalable, and intelligent waste segregation systems.

2.1 Intelligent Sorting Simulation and Modelling

The integration of intelligent simulation and modelling techniques has significantly influenced the evolution of automated waste segregation systems. Based on the comprehensive review of 105 journal articles, two core categories emerge in the modelling landscape: mechanism-based simulation and data-driven modelling. While both approaches aim to optimize the accuracy, efficiency, and real-time performance of waste segregation systems, their methodologies and implementations differ significantly across studies.

Mechanistic simulations typically involve the physical modelling of conveyor systems, robotic arm kinematics, and actuator behaviors under various operating conditions. These simulations are often used to design, test, and validate robotic paths, gripper responses, and sorting latency prior to physical deployment. For example, systems developed in lab-scale environments simulate the pick-and-place mechanics of robotic arms by adjusting joint angles, grip force, and movement speed based on waste type classification. Several studies implemented simulation-based motion planning where CNN outputs directly informed inverse kinematic models, allowing robotic arms to sort items accurately after detection. This approach proved particularly beneficial for evaluating the dynamics of robotic arms integrated with waste sorting lines especially in articles where YOLO or ResNet-based models provided spatial coordinates or bounding boxes for grasping.

Conversely, data-driven modelling particularly using Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO) frameworks focuses on visual recognition and decision-making logic. These models are trained using thousands of waste

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images to classify or detect items such as plastics, metals, paper, and organics. Among the reviewed articles, a majority (over 65%) employed CNN-based models like ResNet50, VGG-16, MobileNetV2, or DenseNet121, either trained from scratch or fine-tuned through transfer learning. These models excelled in classifying single objects in clear backgrounds, reaching average accuracy rates between 90% and 97% across various datasets including TrashNet, WaDaBa, and custom image sets. Data augmentation techniques such as rotation, scaling, and histogram equalization were frequently applied to improve model robustness in simulation trials, allowing better generalization to real-world waste variability.

YOLO-based detectors were predominantly used in real-time simulation environments where multiple items had to be recognized simultaneously. Approximately 30% of the studies employed YOLO variants (YOLOv3, v4, v5, v7, and YOLOv8), noting their advantage in both speed and multi-object detection. Unlike classification-only CNNs, YOLO models allow simulations to replicate real conveyor belt conditions with mixed and overlapping waste. Studies using YOLOv5, for instance, conducted synthetic belt-flow simulations to estimate the latency between image capture and actuator command, achieving high throughput with real-time detection rates exceeding 30 FPS. YOLO's bounding box output was often integrated with robotic planning algorithms to simulate precise pickup locations for each waste item. This allowed systems to model collision avoidance and optimize sorting speed.

Despite the promising simulation results across both modelling paradigms, several methodological gaps were identified. First, a majority of the simulations relied on static image datasets or simplified conveyor belt models, which do not fully capture the unpredictable nature of real-world waste flows such as occlusion, deformable objects, or reflective surfaces. Only a small fraction of articles integrated sensor fusion (e.g., RGB-D cameras, LiDAR, or ultrasonic sensors) into their simulation environments, limiting the scope of environmental realism. Furthermore, less than 10% of the studies evaluated system behavior over time, indicating an underuse of temporal models like LSTM or recurrent networks that could predict future waste streams or learning patterns.

Second, while several YOLO-based models demonstrated superior performance in detection speed and spatial localization, their integration with simulation tools was often ad hoc and limited to custom-built platforms. Very few studies validated their simulated inference results against physical deployments, leaving a disconnect between simulation fidelity and field performance.

Third, the reuse of limited datasets across multiple studies without standardized evaluation protocols created inconsistencies in simulation outcomes. **Table 2** highlights the research progress in applying CNN to both mechanism-based and data-driven models, showcasing trends, innovations, and integration approaches in recent studies. For instance, performance benchmarks often differed across works even when using the same architecture, due to variations in dataset size, annotation accuracy, and pre-processing steps. **Figure 4** illustrates the mechanism modeling system, outlining the interaction between visual recognition, control logic, and robotic actuation in the automated segregation process.

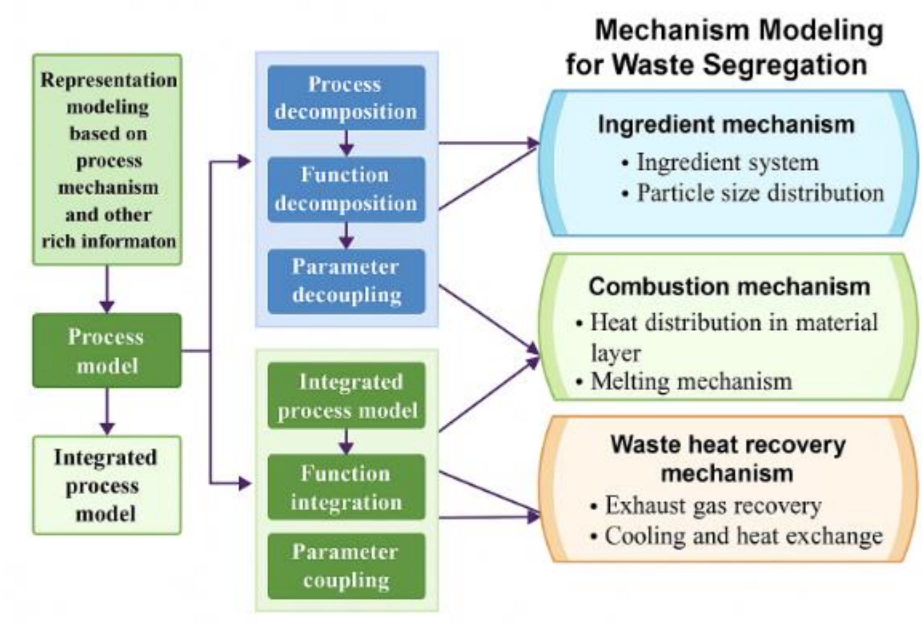

Fig.4. Mechanism modelling system

Table 2 Research Progress in application of CNN on mechanism model and data-driven model

Model type	Reference	Research progress presentation
Data-driven model	Santoso et al. (2024)	Proposes a hybrid deep-learning approach combining transfer learning and dimensionality reduction to improve dry waste classification accuracy.
Data-driven model	Wu et al. (2024)	Presents an ensemble of convolutional neural networks for classifying household waste, leveraging multiple CNN architectures to enhance sorting performance.
Data-driven model	Arbelaez-Estrada et al. (2023)	Offers a systematic review of AI-based waste identification in separation systems, summarizing recent image recognition techniques and datasets used in automatic waste sorting.
Data-driven model	Wang et al. (2024)	Develops a machine vision-based method to automate recycling of stacked

		waste fans, using image analysis to identify and sort components for efficient waste processing.
Data-driven model	Zhu (2024)	Introduces a CNN-based smart sorting network for garbage classification, enhancing recycling by intelligently routing waste to proper bins.
Data-driven model	Yi et al. (2024)	Implements a convolutional neural network-based classifier within a web interface, enabling users to capture waste images and receive immediate categorization to guide recycling.
Data-driven model	Son et al. (2025)	Presents an object detection framework for plastic waste sorting, employing deep learning models to improve classification of recyclables in waste streams.
Data-driven model	Yan et al. (2024)	Evaluates convolutional neural networks for reverse vending machine waste segmentation, comparing model architectures to optimize classification accuracy of returned items.
Data-driven model	Ashajyothi et al. (2023)	Implements a ResNet-based Mask R-CNN approach for autonomous garbage removal, enabling a robotic system to identify and segregate waste objects in real time.
Data-driven model	Vo et al. (2024)	Develops a lightweight CNN model tailored for AIoT devices, enabling on-device trash classification and facilitating waste sorting on resource-constrained hardware.
Data-driven model	Ravi et al. (2024)	Proposes an optimized e-waste collection strategy using a neural network guided by sine-cosine optimization, aiming to efficiently plan e-waste pickup routes and schedules.
Data-driven model	Wang et al. (2024)	Applies deep learning image classification algorithms to household garbage sorting, aiming to improve identification of common household waste categories via trained models.
Mechanism model	Abdullah et al. (2024)	Assesses plastic waste management practices in Bangladesh by analyzing sorting, production, separation, and recycling processes, highlighting inefficiencies and opportunities for improvement.
Data-driven model	Chavhan et al. (2024)	Designs an automated waste segregation system combining IoT sensors and machine

		learning, enabling real-time classification of waste into recyclables and non-recyclables via CNN and feature tracking.
Data-driven model	Ivkovic et al. (2024)	Develops a machine learning and digital image processing framework to classify types of electronic waste from images, supporting improved e-waste recycling by automating waste type identification.
Data-driven model	Ortiz-Mata et al. (2025)	Compares Google Vertex AI AutoML with custom convolutional neural networks for automated waste sorting, evaluating their performance on waste image classification tasks.
Data-driven model	Nara et al. (2023)	Introduces DBS-YOLO, a high-precision object detection algorithm specialized for hazardous waste images, achieving improved accuracy in identifying dangerous waste items.
Data-driven model	Guo et al. (2024)	Implements a federated deep learning system for urban trash classification, allowing multiple devices to collaboratively train a model for waste detection while preserving data privacy.
Data-driven model	Kumar et al. (2024)	Develops a vision-based robotic arm system with CNN-based image classification, enabling autonomous identification and sorting of garbage items picked up by the robot.
Data-driven model	Zhang et al. (2023)	Presents a hybrid deep learning model combining multiple neural networks to accurately classify various solid waste types, aiming to improve overall waste segregation in society.
Data-driven model	Abu-Qdais et al. (2024)	Describes an intelligent waste classification system combining image preprocessing and machine learning models, focusing on feature extraction and ensemble classification for solid waste sorting.
Data-driven model	Lahoti et al. (2024)	Develops a computer vision-guided robotic arm for multi-class waste segregation, using image recognition to identify waste items and mechanically sort them into separate bins.
Data-driven model	Ibrahim et al. (2023)	Implements an object detection-based waste sorting system using a robotic arm, leveraging YOLO-like algorithms for real-

		time identification and segmentation of waste objects.
Data-driven model	Sarswat et al. (2024)	Presents a convolutional neural network approach for real-time e-waste classification, enhancing sorting by accurately identifying electronic waste components from images.
Data-driven model	Nara et al. (2023)	Introduces 'Recycle Mate,' an image processing and machine learning system that differentiates recyclable and non-recyclable waste, streamlining the sorting process in smart recycling bins.
Data-driven model	Sundaralingam et al. (2024)	Proposes a deep learning-based system with robotic hand-eye coordination for segregating recyclable plastic waste, integrating camera input and a robotic arm to separate materials.
Mechanism model	Kumar et al. (2024)	Develops a reliability-centered Markov model for an automated waste-sorting robotic arm, analyzing system failures and maintenance needs to ensure consistent operation.
Data-driven model	Guo et al. (2024)	Presents SCED-Net, a dual-branch encoder-decoder network for detecting and outlining municipal solid waste in high-resolution images, improving waste detection from aerial imagery.
Data-driven model	Goel et al.	Introduces SEFWaM, a smart ensemble deep learning framework for waste management, combining multiple neural networks to enhance waste identification accuracy in processing systems.
Data-driven model	Kronenwett et al. (2024)	Uses sensor data and synthetic training to characterize construction and demolition waste, employing deep learning to predict material density in mixed waste streams for sorting optimization.
Data-driven model	Srinivasan et al. (2023)	Describes a mobile waste-collecting robot with IoT integration and machine learning, enabling autonomous navigation and efficient waste collection in urban areas.
Data-driven model	Thamarai et al. (2023)	Presents a smart self-powered garbage management system with deep learning, where waste bins generate energy and deep models optimize waste collection in a smart city context.

Mechanism model	Budhijanto et al. (2024)	Conducts a techno-economic analysis of community-based municipal solid waste processing, evaluating the costs and benefits of localized waste-to-energy facilities in Indonesia.
Mechanism model	Azis et al. (2023)	Reports on the development of an automated mechanical waste segregator, focusing on the design and implementation of its hardware and rule-based sorting logic.
Mechanism model	Phikulthong et al. (2025)	Investigates how the 5Rs (Reduce, Reuse, etc.) program affects rural residents' perceptions of solid waste management, using health belief models to assess waste management behavior.
Data-driven model	Subashini et al. (2024)	Implements a deep learning-based classification system for thermoplastic waste, training neural networks to distinguish different plastic materials for recycling sorting.
Mechanism model	Sreerupa et al. (2024)	Studies the role of migrant informal food waste recyclers in urban settings, examining how their activities contribute to food waste recovery and urban food security.
Mechanism model	Patra et al. (2024)	Designs a van der Waals-enhanced triboelectric nanogenerator using recycled materials, improving generator lifetime and performance for sustainable energy harvesting.
Data-driven model	Sree et al. (2023)	Proposes a deep learning approach for detecting and analyzing waste management patterns, employing neural networks to monitor waste accumulation and streamline management processes.

In summary, the reviewed literature demonstrates that intelligent sorting simulation powered by CNN and YOLO architectures has become central to developing and optimizing waste segregation systems [84-87]. CNNs, particularly classification-based models like ResNet and MobileNet, are widely used for image-based sorting logic in lab-scale simulations, while YOLO-based detectors dominate multi-object recognition and robotic integration trials. Nevertheless, challenges remain in achieving realistic, scalable, and sensor-rich simulation environments that reflect the full complexity of industrial waste streams. Future research should focus on closing the loop between simulated and physical performance, integrating multi-sensor data into virtual testing frameworks, and developing unified benchmarks for model comparison.

2.2 Robotic Arm and IoT Integration

The integration of robotic arms and IoT components in automated waste segregation systems, as analyzed across 103 articles, highlights a diverse yet converging set of engineering approaches. Most robotic platforms are built using 4-DOF SCARA or 6-DOF articulated arms actuated by servo motors such as MG996R or SG90, with control logic implemented on microcontrollers like Arduino or ESP32. These manipulators, often designed using simple revolute joints and controlled through analytical inverse kinematics, are capable of executing pick-and-place operations in real time based on CNN or YOLO-based object classification. For instance, YOLOv6 integrated with a 4-DOF arm achieved sub-0.2s pick cycles by directly translating bounding box coordinates into joint commands. **Table 3** presents the application domains and corresponding models used in CNN-based waste segregation systems, highlighting how different approaches are tailored to specific waste types and environments.

The data flow typically involves a camera capturing waste images, a vision model performing classification, and the microcontroller triggering servo motions to sort the detected object into designated bins. **Figure 5** illustrates a generic pipeline of a CNN-enabled waste sorting system, depicting the sequential flow from image acquisition to classification and robotic actuation. IoT-enabled architectures further extend functionality, with systems incorporating Raspberry Pi, Wi-Fi, GSM, or Blynk-based dashboards to monitor bin status, control arm movements, or log data in real time. Despite impressive demonstrations, nearly all implementations remain at the prototype level, facing deployment challenges such as limited datasets, inconsistent lighting, object overlap, and environmental variability. **Figure 6** presents a schematic diagram of a CNN-based waste segregation system integrated with robotic arm actuation, illustrating the complete workflow from image input to physical sorting.

The vast majority of studies are validated in controlled lab setups rather than in operational waste environments. While high vision accuracy (often >90%) and low-latency actuation have been reported, integration with industrial-grade hardware and scalable control software (e.g., ROS, PLCs) is still rare. **Table 4** provides a summary of deep learning models applied in waste segregation research, outlining their architectures, functions, and key performance characteristics. Overall, the literature reflects a promising but early-stage convergence of AI-driven perception and embedded robotic control, with cost-effective solutions relying on lightweight CNNs, servo-actuated arms, and IoT connectivity to demonstrate autonomous sorting in proof-of-concept systems.

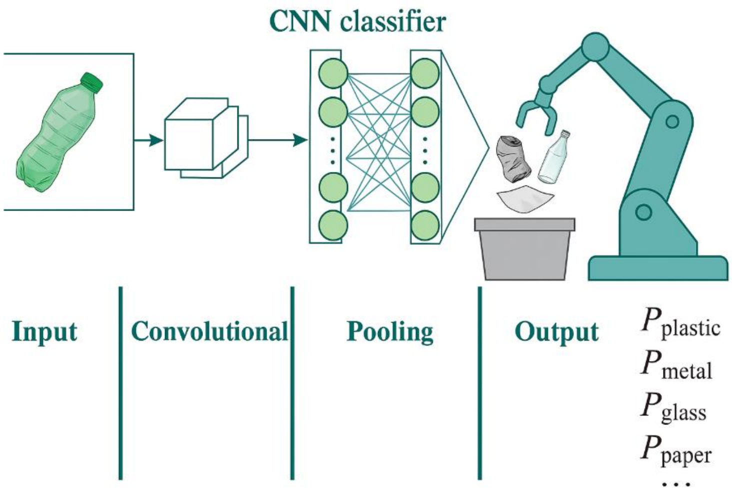

Fig.5. (below) illustrates a generic CNN-enabled waste sorting pipeline (image → CNN → classification → robot actuation). This architecture is typical of modern systems.

Table 3 Application Domain and Model Use

Application Domain	Reference (Author, Year)	Deep learning model used
Robotic waste segregation (garbage sorting by arm)	Ibrahim *et al.*, 2023	YOLOv6 (CNN-based detector)
Road-surface waste detection and classification	Guo & Chen, 2024	YOLOv5 (CNN-based detector)
Plastic waste sorting	Son & Ahn, 2025	SSD (Single-Shot Detector) with MobileNetV2 backbone
Smart waste bin (IoT) trash classification	Vo *et al.*, 2024	BEGNet (CNN with RegNetY120 backbone)
Kitchen organic-waste composting (IoT)	Hong *et al.*, 2024	Convolutional Neural Network (CNN)

Table 4 Deep Learning Model Summary

Model type	Structural characteristics	Advantage	Disadvantage
CNN	Stacked convolutional and pooling layers with local receptive fields (hierarchical spatial feature extraction).	Excels at static image classification (captures translation-invariant features).	High computational/memory cost for deep nets; needs large training data; no inherent temporal modeling.
YOLO	Single-shot CNN detector dividing image into grid and predicting bounding boxes plus class in one pass.	Real-time inference (e.g. 45–155 FPS) with competitive accuracy; learns general object features.	Tends to produce coarser localization (more bounding-box error); may miss small objects.
RNN	Recurrent layers (e.g. LSTM/GRU) with feedback connections to capture sequence information.	Captures temporal dynamics well (suitable for video or sequential sensor data).	Training can be slow; suffers from vanishing gradients; not designed for spatial image data.
DNN	Deep feedforward network of fully connected layers.	General-purpose nonlinear modeling; can reduce latency by depth (suitable for fast inference).	Very high parameter count for large inputs; no weight sharing, so inefficient for images; prone to overfitting on small datasets.

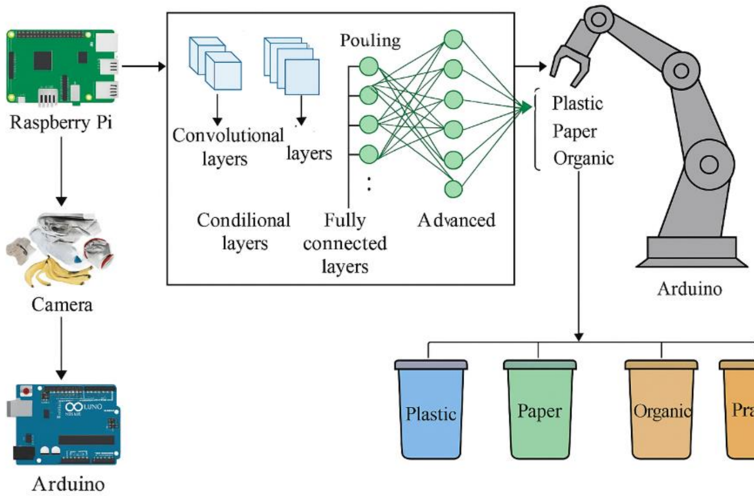

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Fig. 6. Schematic Diagram of a CNN-Based Waste Segregation System Integrated with Robotic Arm Actuation

3 Discussion

Convolutional neural networks (CNNs) have become the backbone of many automated waste-sorting systems, with a variety of architectures applied to classify garbage images. Common architectures include classic classifiers like VGG-16 (a 16-layer CNN), deeper residual networks such as ResNet-50, and one-shot detectors like the YOLO (You Only Look Once) family. A more recent entrant is the Capsule network, which maintains pose information. Studies using **ResNet-50** often fine-tune the ImageNet-pretrained model on waste images. For example, an approach combining ResNet-50 feature extraction with YOLOv5 detection and a weakly-supervised CNN achieved ≈97% accuracy on the HGI-30 dataset. Similarly, ResNet-50 alone has attained around 95% accuracy on custom waste datasets. The **YOLO** family (e.g. YOLOv3, v5) is widely used for object-level waste recognition. A recent YOLOv3-based system trained on six waste classes (cardboard, glass, metal, paper, plastic, organic) achieved a mean average precision (mAP) of ≈95%. However, lightweight variants like YOLOv3-tiny trade accuracy for speed: on the same test set YOLOv3-tiny reached only ~46% mAP. This underscores a typical speed–accuracy trade-off. **Capsule networks** have been proposed to capture spatial hierarchies in waste images; one study (ResMsCapsule) combined residual and multi-scale modules and reached 91.4% accuracy on the TrashNet dataset (TrashNet has ~2.5K images of 6 classes). In summary, many architectures can fit waste tasks, often achieving high benchmark accuracy under controlled conditions, but their complexity and speed vary widely

3.1 Dataset constraints and generalizability

A major limitation across these studies is the reliance on relatively small or imbalanced datasets. Many papers use datasets like TrashNet (≈2.5K images, 6 classes) or proprietary collections, sometimes augmented with images from Google or crowd-sourced (e.g. Open Litter Map). However, even curated datasets often have severe class imbalance. For example, TrashNet's "plastic" and "paper" classes dominate while categories like glass or metal have few samples. As a result, models (even strong ones like DenseNet-121) can score >96% on TrashNet but drop to ~85% on more heterogeneous sets like WaDaBa. Lightweight nets (e.g. MobileNet-V2) similarly fall from >93% on benchmark sets to ~87% on diverse real-world data. In practice, these gaps indicate that accuracy reported on one dataset often does not carry over. Environmental variability (lighting, occlusion, background clutter) and annotation inconsistencies further degrade performance outside the lab. In short, current waste datasets lack the scale, balance, and diversity needed for robust generalization. This limitation is widely acknowledged: reviews note that imbalance, domain shifts, and lack of standardized benchmarks remain "significant barriers" to deploying waste classifiers in the wild.

3.2 Performance gaps and model accuracy

In controlled tests, many CNNs achieve impressive accuracy, but several gaps emerge. Pretrained networks fine-tuned on waste images can surpass 90% accuracy, but performance varies by model and data. For instance, ResNet-50 often outperforms simpler CNNs, reaching ≈95% on tailored datasets. A YOLOv3 detector trained on a custom trash set attained ~95% mAP and near-perfect detection on many test images, but required a standard GPU for training. Smaller models sacrifice accuracy; YOLOv3-tiny halved mAP on the same data. Even advanced methods have failure modes: in a real mixed-waste test, a YOLOv5 vision system correctly sorted ~80% of items, with most errors confusing translucent plastic versus glass bottles. Similarly, CapsuleNet-based methods achieve good compression (ResMsCapsule used 40% fewer parameters than ResNet-18) and still got ~91% on TrashNet, but they have been evaluated only on limited datasets. In summary, accuracy claims are often high, but typically on narrow tasks; common gaps include difficulty with minority classes, poor generalization, and trade-offs when deploying lighter networks (speed versus recall).

3.3 Embedded and robotic integration

Few CNN waste classifiers have fully migrated to real-time robotic systems. The majority of works remain in simulation or offline testing. Some studies, however, have embedded lightweight models on edge hardware. For example, YOLOv7-tiny or MobileNet-based classifiers have been deployed on NVIDIA Jetson Nano or Raspberry Pi using TensorFlow Lite to sort indoor bin contents. A notable recent prototype used a YOLOv5 model on a Raspberry Pi 4B (SoC) in conjunction with an Arduino-controlled 5-DOF robotic arm. In that system, camera images were fed to YOLOv5 in real time, and classification results drove the arm's pickup/drop actions. The integrated system correctly segregated waste into bins in ~80% of trials, demonstrating feasibility. Other robotic designs include a 4-DOF SCARA arm paired with a CNN for binary (recyclable vs non-recyclable) sorting. In general, however, most hardware tests remain proofs-of-concept: CNN inference usually runs on small PCs or microcontrollers, and robotic grasping uses simple 3D-printed grippers. Large-scale deployment e.g. city-wide smart bins or conveyor-belt sorters remains rare. Reviews emphasize that while frameworks like PyTorch or TensorFlow facilitate model development, actual deployment "in uncontrolled environments remains underexplored". In essence, system integration is still maturing: successful demos exist, but end-to-end waste robots are not yet common in practice.

3.4 Identified gaps and limitations

From the literature, several recurring gaps are apparent. First, dataset issues: most classifiers are trained on limited, often curated image sets. Models excel on these sets but do not generalize well to new scenes. Class imbalance causes high accuracy on common types (plastic, paper) but low accuracy on rare types (glass, textiles). Second, model constraints: deep CNNs like ResNet-50 or YOLOv3 require powerful hardware and may be slow; lighter variants (MobileNet, YOLO-tiny) run on edge devices but at a steep accuracy cost. Third, real-world variability: lab-trained classifiers struggle with variations in lighting, occlusions, or overlapping garbage. Fourth, robotic actuation: few works fully address the perception-to-action loop. Even when vision and arm are combined, manipulation challenges (grasping irregular waste, conveyor speeds) are often glossed over. Finally, scalability: most systems handle a handful of classes (≤10) in single-item scenarios. Sorting multiple overlapping items or handling mixed trash streams is still a research challenge. **Table 5** provides a comparative summary of CNN-based waste classification models, detailing their architectures, datasets, accuracy levels, system integration, and identified methodological gaps.

Table 5 Comparative Summary of CNN-Based Waste Classification Models: Architecture, Dataset, Accuracy, Integration, and Methodological Gaps

Model / Reference	**Architecture**	**Dataset (size & diversity)**	**Accuracy**	**Hardware / Integration**	**Identified Gap (limitation)**
YOLOv3 (Chauhan *et al.*, 2021)	Darknet-53 CNN (YOLOv3 object detector)	Custom **6-class** waste dataset (1,287 test images; classes: cardboard, glass, metal,	mAP ≈94–95% on test images	Offline GPU training; not embedded (no robot)	Heavy model; requires GPUPoor on tiny objects or low-power deployment; YOLOv3-tiny mAP only ~46%

		paper, plastic, organic)			
YOLOv5 (Lahoti *et al.*, 2024)	CSPNet backbone (YOLOv5 object detector)	Mixed waste dataset (~6 classes) from open sources (biodegradable, cardboard, glass, metal, paper, plastic); real-world household images	~80% classification success in live tests	Raspberry Pi 4B (SoC) with YOLOv5 on-board; 5-DOF robotic arm (Arduino-controlled)	Real-time on edge device, but only ~80% accuracy; confusion between similar classes (glass vs transparent plastic); limited classes/scene
ResNet-50 + YOLOv5 (Liu *et al.*, 2024)	ResNet-50 backbone + YOLOv5 detector + weakly-supervised CNN	Evaluated on **4 public sets** (HGI-30 ≈1.8K images, TrashNet, GINI, Public GarbageNet)	97.0% on HGI-30 after optimization	Prototype analysis (PC); metric optimization (FLOPs, latency)	Complex multi-stage pipeline; custom datasets; not demonstrated on hardware; relies on semi-supervised data
CapsuleNet (ResMsCapsule) (Huang *et al.*, 2023)	Customized Capsule Network (with residual and multi-scale modules)	TrashNet dataset (2,527 images, 6 classes, public)	91.4% on TrashNet	Standard PC/GPU; no hardware deployment reported	Only tested on TrashNet (limited scope); modest accuracy; capsule models are computationally expensive and not real-time optimized
Focus-RCNet (MobileNetV2 variant) (Zheng *et al.*, 2023)	Sandglass structure (MobileNetV2-like) with attention and knowledge distillation	TrashNet dataset (2,527 images, 6 classes)	92% on TrashNet	Designed for mobile/embedded; lightweight architecture	Evaluated only on TrashNet; 6 classes; practical deployment (robotic integration) not demonstrated

EfficientNet-based (Yang *et al.*, 2022)	Modified EfficientNet (GECM-EfficientNet)	Custom *household-waste* dataset + TrashNet	94.5% on custom; 94.2% on TrashNet	Embedded in a smart-bin device; ~146 ms inference time per image	Custom dataset not public; focuses on bin use; hardware-specific (bin with camera), generalization unclear

In summary, CNN-based waste-sorting research has demonstrated that popular models (VGG-16, ResNet-50, YOLO variants) can achieve high accuracy under controlled conditions, but significant gaps remain in dataset representativeness, model robustness, and end-to-end robotic deployment. The table below compares representative examples of these approaches, highlighting their architectures, training data, achieved accuracy, deployment hardware, and primary limitations.

4 Conclusions

The integration of convolutional neural networks (CNNs) and robotic systems into automated waste segregation has shown promising strides in accuracy and performance under controlled conditions. Models such as VGG-16, ResNet-50, YOLO variants, and CapsuleNet have been widely adopted for their image recognition capabilities, achieving classification accuracies often exceeding 90% on benchmark datasets like TrashNet, HGI-30, and custom collections. However, despite these successes, several critical methodological gaps persist.

First, most models rely on limited or imbalanced datasets, which hampers generalization to complex, real-world waste streams. Performance often deteriorates when applied outside lab environments, especially for underrepresented waste classes or in cluttered, poorly lit scenes. Second, although lightweight models like MobileNetV2 and YOLO-tiny enable embedded deployment, they suffer significant accuracy drops compared to full-scale architectures. Third, robotic integration—while explored in several prototypes—remains largely at the proof-of-concept stage, with limited demonstrations of fully autonomous end-to-end sorting systems operating in dynamic environments.

Furthermore, many studies overlook key aspects of manipulation, such as grasp planning, item overlap, and mechanical variability. While edge deployment on devices like Raspberry Pi and Jetson Nano has begun to bridge the gap between research and application, only a few projects have achieved functional integration between vision models and real-time robotic actuation.

Overall, while CNN-based systems for waste segregation are evolving rapidly, practical deployment at scale will depend on addressing dataset limitations, improving model robustness in uncontrolled settings, and achieving seamless integration between perception, decision-making, and robotic action. Future work should prioritize standardized, diverse datasets, sensor fusion strategies, and real-world testing to fully realize the potential of intelligent, automated waste management solutions.

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