International Journal on Interactive Design and Manufacturing (IJIDeM)
https://doi.org/10.1007/s12008-023-01320-w

REVIEW

A state-of-the-art review on robotics in waste sorting: scope and challenges

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Received: 6 January 2023 / Accepted: 2 April 2023

Abstract

An essential component of a waste management system is waste sorting. Correct sorting of waste is crucial for creating a clean environment for everyone, reducing pollution and reusing recyclable materials. Manual waste sorting can cause serious health issues to the workers due to various disease-causing agents present in the garbage. The use of robots in sorting of materials such as glass, paper, plastic, metals, etc., from other waste can facilitate the production of secondary raw materials as well as conserve energy and production costs. Robots can help in efficient sorting of waste and can work endlessly thus eliminating health hazard to labours. By using computer vision, artificial intelligence, and automation systems, both, the efficiency and accuracy of waste sorting can be increased. This paper showcases the recent studies related with implementation of robots in waste sorting for efficient recycling, algorithms, types of grippers and its advancements. Various studies have been discussed related to computer vision and comparison of various algorithms is also presented. Major challenges faced in implementation of robotic sorting on global scale and its future scope has also been discussed.

Keywords Robotic waste sorting · Deep learning · IoT · Object detection · Artificial intelligence · Robotic grippers

Abbreviations

IoT	Internet of Things
IR	Infrared
ML	Machine learning
DL	Deep learning
CNN	Convolution Neural Network
R-CNN	Region-based Convolution Neural Network
SSD	Single Shot Multiproxy Detector
FCOS	Fully Convolutional One-Stage object detection
KNN	K nearest neighbour
SVM	Support Vector Machine
SLAM	Simultaneous Localization and Mapping
IoT	Internet of Things
Dof	Degree of freedom
SUS	System Usability Scale
COCO dataset	'Common Objects in Context' dataset
MAP	Mean Average Precision
PET	Polyethylene terephthalate
HDPE	High Density Polyethylene
LDPE	Low Density Polyethylene
PP	Polypropylene
PS	Polystyrene
GUI	Graphical User Interface
LiDAR	Light Detection and Ranging
DOF	Degree of freedom
MSWM	Municipal Solid Waste Management

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Published online: 06 May 2023

1 Introduction

Waste management and segregation are vital processes in urban areas and metropolises. Trash including various non-biodegradable materials, if not recycled, can cause serious harm to the environment as well as spread several diseases [1]. In regional, remote, and isolated towns, inadequate recycling and landfill infrastructure, limited access to markets for recyclable materials, insufficient or non-existent collection and recycling services, and a shortage of local knowledge all contribute to the problem of poor waste management [2].

India generates solid waste approximately 42.0 million tons annually, according to research. Also, waste management in India depends only on landfills and informal sectors, which is not sufficient to overcome its waste generation. According to the Planning Commission Report, by 2031, the urban cities in India will generate 165 million tons of waste per year. This value could touch 436 million tons of waste by 2050 [3]. To relieve public and environmental concerns, effective waste management measures for segregation, collection, treatment, and disposal must be implemented. Unpleasant greenhouse gases are produced in lowlands when mixed dry and moist garbage decomposes. It is possible to properly use and recycle the trash owing to waste management and efficient sorting [4].

There are various types of plastics where most of them are recyclable. Around 12% of the spent plastic is recycled globally, around 25% is incinerated, but approximately 60% ends up polluting the environment [5]. Glass can be recycled repeatedly and never loses its quality after being recycled. 70% less energy is used when new paper is made from recycled paper stock than while using virgin pulp. Manual waste sorting can cause serious health issues to the workers due to various disease-causing agents present in the garbage [6, 7].

Various technologies used to sort wastes are present such as Eddy current based sorting, Metallic sorting, X-ray based sorting, Optical based sorting, Spectral imaging-based sorting, Laser induced breakdown spectroscopy, etc. [4]. With the current wave of innovation and robotics penetrating almost all sectors, it is noteworthy that use of robots in waste sorting proves to be a great advantage to our society. In this paper we focus on studying the existing systems which implement robots for sorting and segregation of waste using technologies like artificial intelligence [8], Machine Learning [9] and Deep learning [10], which help automize waste detection tasks. This work focuses on reviewing the recent studies involving the contribution of robotics and AI in waste sorting for efficient recycling, its advantages, comparison, challenges faced as well as the future scope of robotics in waste sorting.

The following outlines the scope of the review paper being discussed:

- The major objective of this review paper is to present the most recent robotic applications in automated sorting methods for recovering different recyclable materials like metal, plastic, paper, glass, and wood from garbage.
- Yet, some of the methods covered in this paper might also be used with other waste streams, like industrial trash, electronic waste, and garbage from building and demolition.
- This article mainly surveys journal and conference publications during the period 2010–2023.
- In terms of the variety of materials sorted, the accuracy of the sorting algorithms, the shortcomings of the literature that was reviewed, and other factors, this article examines the waste sorting procedures described in the literature.
- The article also analyses the automated sorting systems, sensors and object detection-based waste detection, study of robot systems and grippers for sorting, and discusses potential areas for further research and improvement.

2 Survey on automatic waste sorting

Sorting garbage is crucial because it can increase the amount of waste that is later recycled, lowering the pollution of the environment and landfills [4]. The dynamic rise in garbage production and the despicable dumping of waste are becoming matters of concern. Automated garbage segregation plays a crucial part in preventing this situation and making recycling easier [11]. The process of automated sorting can be divided into two parts: first is classification or differentiation of the waste into a certain category/class, and the second is the mechanical sorting of the waste according to material. The methodology used in this review paper is shown in Fig. 1.

The paper [12] provides a critical analysis of academic research on computer vision-enabled solid waste sorting. Other papers discuss specific approaches to waste object localization and classification using deep learning algorithms[13] as well as edge-computing video analytics solutions for automated waste detection [14].

In [15], the authors provide an overview of various CNN architectures, including VGGNet, ResNet, and Inception, and discuss their applications in waste identification and classification. In the paper, problems with CNNs for trash identification are discussed, including data limitations and hardware requirements. They have studied several datasets, including WASTE and TrashNet. The potential advantages of CNNs for boosting recycling and reducing waste are emphasized. The ethical implications of alternative ML methods, including reinforcement learning or unsupervised learning, are not investigated. To address these worries and explore alternatives, more study is required. In general, the report offers insightful information about using CNNs in waste management. In paper [12], the authors examine academic

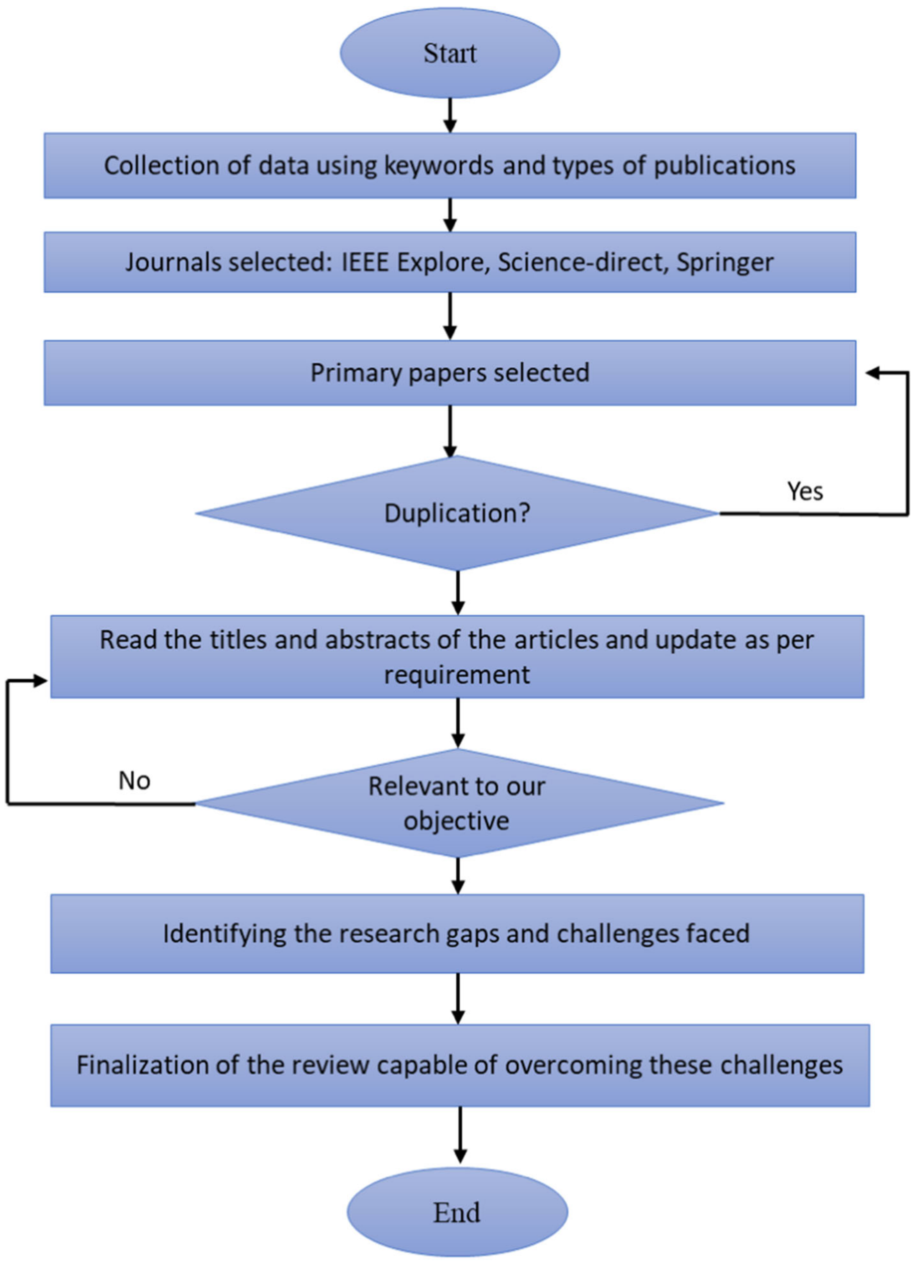


Fig. 1 Research Methodology followed

research published in the past decade and critically evaluate the techniques and approaches used in CV for waste sorting. The authors emphasise the significance of data collection, pre-processing, precise labelling, and real-time processing as well as the requirement for hardware acceleration to reach high sorting speeds.

An in-depth analysis of current research in Computer Vision based solid waste sorting is provided in [12]. However, there are a few research gaps that are not mentioned in the paper. These include:

- Lack of standardization: There is a need for standardization in terms of data collection, annotation, and evaluation metrics to enable fair comparisons between different CV methods.
- Robustness to different waste types: Most of the research has focused on sorting a limited number of waste types, and it is unclear how well these methods would generalize to other waste types.
- Integration with robotic systems: The review paper does not cover the integration of CV for waste sorting with robotic systems, which could potentially automate the entire waste sorting process.

Fig. 2 Keywords of selected papers for literature review

- Environmental impact: The review paper does not cover the environmental impact of CV-based waste sorting systems, such as energy consumption and carbon footprint.

Our paper gives tabular comparison of 32 papers, comparing accuracies of the model used, names of classes detected in the object detection model, different ML/DL models used by the papers and the drawbacks of each study have been mentioned. In the study, not many papers are available related to review on robotic waste sorting and thus our paper can help fill the mentioned gaps and provide better review and comparison of various studies. In Fig. 2, we display the keywords of various papers that were examined in our study.

Figure 3 shows the variation of number of publications surveyed and the year they were published. The figure shows that there is a major rise in the number of publications in the year 2021–2022.

2.1 Waste detection

It is necessary to develop a system for waste detection to classify waste, which can be done by using different types of sensors [16–18] or by using different object detection algorithms [9, 16, 19, 20] and various related studies are reviewed in this section.

2.1.1 Sensor based detection

IoT has played an important role leading to innovations for automizing segregation of waste using various sensors, actuators, etc. One study even shows implementation of IoT to develop an automated device for the separate collection of used absorbent hygiene products [21]. For detection of waste, various sensors are used which help in classification of waste based on different material properties as shown in Fig. 4(a). Metallic sensors are used to detect and separate metal from the waste which helps in recycling of metal cans, containers, batteries, etc. Inductive sensors and electromagnetic sensors

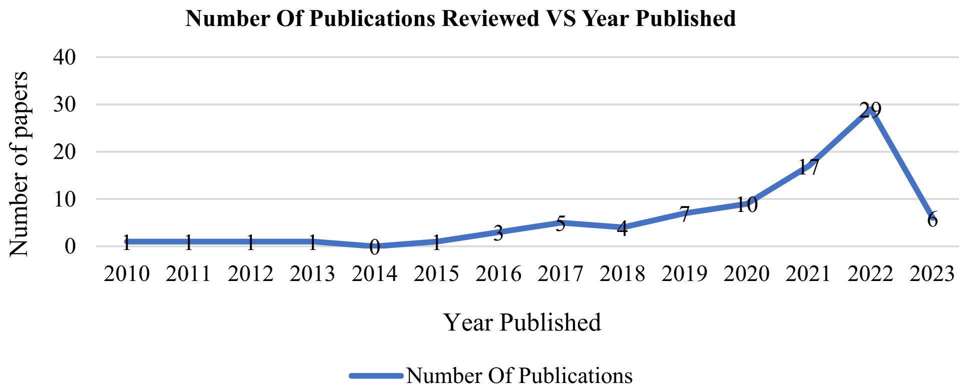


Fig. 3 Number of papers reviewed versus year published

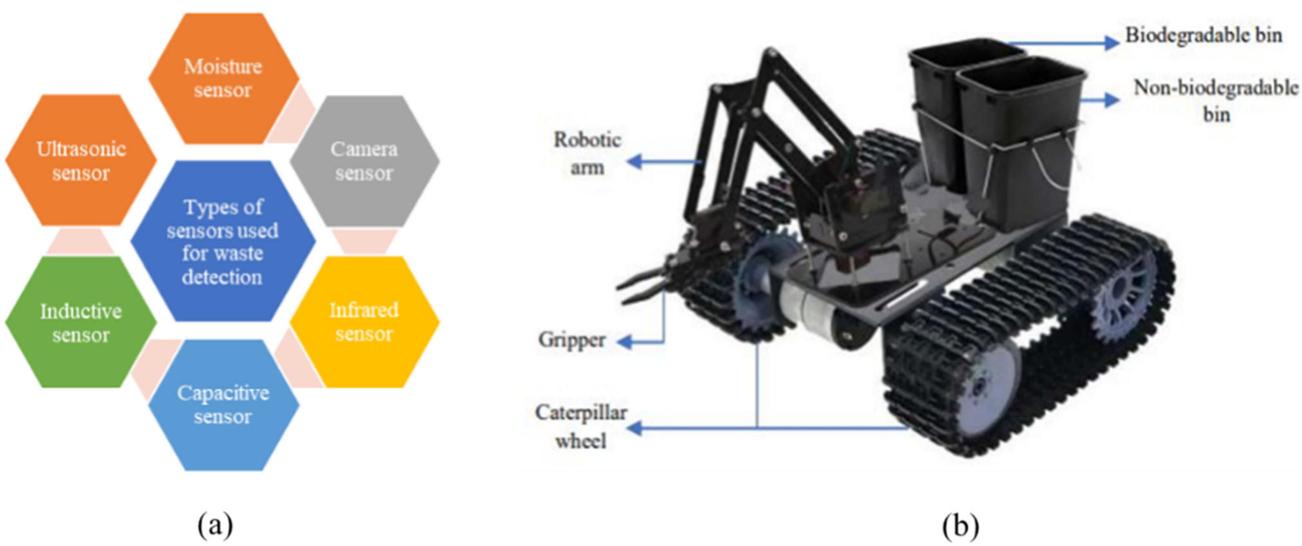


Fig. 4 **a** Different types of sensors for waste detection **b** Robotic arm on a vehicle for trash sorting [25]

work as metal detectors. For non-contact detection, capacitive proximity sensors are used. They can detect both metallic and non-metallic items like liquid, plastic, paper, etc. Ultrasonic sensors are object detecting sensors which help in indicating whether an object is detected or not i.e., any obstacle or level indication.

In [22], the authors have designed a robot vehicle with wheels and robot arm which senses the presence of waste using Infrared (IR) sensor and detects waste using metal, ultrasonic and moisture sensors. Although the study uses metal sensor, in the end, waste is segregated into dry and wet waste category only, which is a major drawback of this study. In [23], the authors have created a robot arm and conveyor system that can sort waste into three categories: plastic, organic, and metal. It uses three sensors: inductive sensor for metallic waste, an IR sensor for presence of any object, and a voltage sensor to distinguish between organic and plastic waste. In [24], the paper proposes a waste tracking system that includes a mechanism to separate household waste into metallic, plastic, and glass categories. It uses inductive proximity sensor to detect metallic waste and capacitive non-contact sensor detects non-metallic waste. In [25], the authors have introduced a system of electronic robotic arm combined with sensors placed on a movable chassis as shown in Fig. 4b. Capacitive proximity sensor, humidity sensor and gas sensor are used to segregate into biodegradable and non-biodegradable waste.

Although, the sensors used assist in segregating waste based on material, colour, odour, moisture, etc., but for segregating waste which varies vastly and has variable materials, shapes, sizes, the object detection method proves to be more efficient and accurate method of segregating waste into different categories.

2.1.2 Computer vision based object detection

Waste sorting using Computer Vision (CV) has been envisioned and researched for more than two decades [12]. Waste detection has become an important area of research, with applications in environmental monitoring, recycling, and waste management. Machine learning (ML) and Deep learning (DL) algorithms have been used to develop automated waste detection systems that can identify different types of waste and classify them for further processing. ML is a subfield of artificial intelligence that involves the use of algorithms and statistical models to enable computer systems to improve their performance on a specific task through experience. DL is a subset of ML that uses artificial neural networks with multiple layers to learn representations of data, and is particularly well-suited for complex problems like image and speech recognition. The adoption of AI applications is a tool to accelerate sustainable solid waste management [26].

Object detection is a technique used for classifying objects in images using image processing, machine learning, and deep learning [27]. Generic object detection is used to develop a general-purpose algorithm for detection with high accuracy and high efficiency [28]. Convolutional neural networks (CNNs) are a type of deep learning algorithm that is widely used for object detection, and models like R-CNN, Faster RCNN, SSD, Fast RCNN, YOLO models [29], and FCOS [30] are popular CNN-based models for object detection. YOLOv7 is the latest and most accurate and fast model for object detection [31]. The use of optical sensors like RGB and depth cameras along with deep learning algorithms [32] for object detection and classification. These techniques are being applied to different waste materials such as plastic, metal, glass, etc. [33] to accurately segregate them.

Various deep learning models are being studied and tested on datasets of different waste materials to improve the accuracy of detection and classification. Based on the review done, we can say that the different ways in which waste can be classified and segregated, is shown in Fig. 5.

In [34], as shown in Fig. 6a and b, the project aims to create an automated waste identification system utilising deep learning algorithms that collect waste images/videos from camera and classify into different classifications and orientations. Out of 507 photos, the model correctly predicted 461 of them, giving it a 91% accuracy rate.

The papers [35–37] and [38] propose different deep learning models for detecting and segregating garbage into various categories. In [35], a robotic vehicle, shown in Fig. 7a is developed that uses a CNN network with 15 layers for automatic segregation of plastic trash into seven types [36]. Presents a training batch for the YOLOv7 algorithm for garbage detection [37]. Proposes the i-YOLOX model for detecting domestic wastes, which enhances the YOLOX-S model by increasing FPS, decreasing the number of parameters, and enhancing mean average precision by 1.47%. The upgraded model accurately detects garbage in natural situations [38]. Suggests using an enhanced YOLOV4 network framework for finding 15 objects in 3 categories with an average accuracy of 64% and 92 frames per second. The upgraded YOLOV4 is suitable for embedded systems and can accurately recognize garbage categories.

They use datasets consisting of various types of non-decomposable garbage data such as chips packets, plastic bottles, and polythene [36]. The study in [39] demonstrates the superiority of YOLOv7 over other object detection models. Some papers propose GUI-based systems for waste classification that can differentiate between different forms of trash, including dry, moist, and vehicular waste. The dataset can be expanded with more images to improve the system's accuracy. Another paper depicting superiority of YOLOv7 uses common home waste such as peels, bottles, cigarettes, glass, and batteries for algorithm research, with a dataset consisting of 2400 data bits with various shooting angles, scenes, and degrees of degradation, etc. [40].

Various other research papers have been mentioned in Table 1, where the different types of sensors used, type of waste material detected, types of algorithms (object detection models) used, their accuracies and drawbacks in those studies are studied and compared.

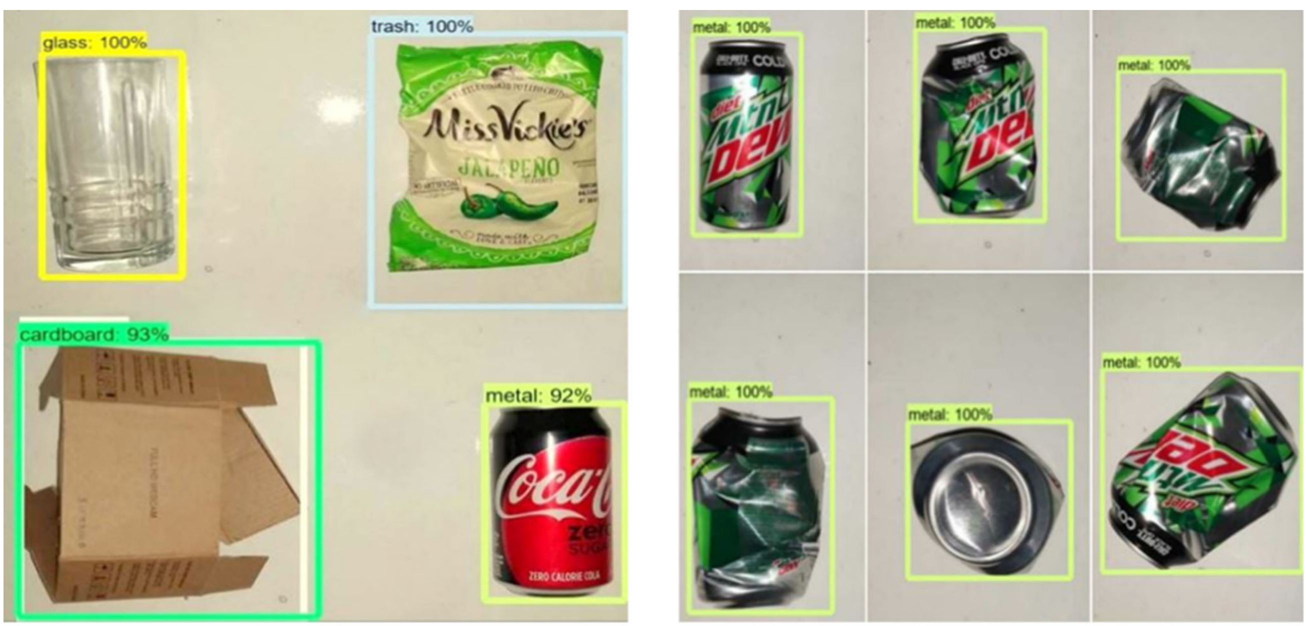
The authors cover the evolution of object detection from traditional computer vision methods to deep learning-based approaches and provide a detailed description of various object detection frameworks such as R-CNN, Fast R-CNN, Faster R-CNN, YOLO, and SSD. The paper also includes a discussion on various datasets used for evaluating object detection models, along with a performance comparison of different deep learning models on these datasets. The authors conclude that deep learning-based approaches have achieved superior performance compared to traditional computer vision methods, and that there is still room for improvement in terms of robustness and generalization of these models.

Figure 8 shown in depicts the different object detection models used in various papers reviewed along with their accuracies of waste detection. ResNet-50 (CNN) algorithm [41] gives the highest accuracy of 98.53%.

2.2 Sorting mechanisms

The next step after waste detection is the physical automated sorting of waste. The study in [62] aims to explore MSWM technological barriers under I4.0 practices by which satisfactory achievement of a new smart and sustainable municipal management. There are various types of waste sorting mechanisms such as Eddy current based, robotic arm based, Eddy current based, Laser Induced Breakdown

Fig. 5 Different classes of waste for object detection



(a) (b)

Fig. 6 **a** Multi-object waste detection using faster R-CNN **b** detection with different orientations [34]

Spectroscopy, Optical based, Conveyor based and Spectral imaging-based sorting [63].

2.2.1 Automated waste sorting techniques

In manual waste sorting, the pickers use human eye inspection to identify each type. The size of the object to be grasped, the depth of the combined garbage on the conveyor, and the conveyor's speed all have an impact on the ability to identify objects. Various sensors and material handling technologies can be applied to the automated sorting of recyclable trash, depending on the materials in question. A spot automated garbage sorting system is created in [64] to separate metal, dry, and wet garbage. The metallic garbage is separated using a parallel resonance impedance device, and the moist and dry waste are separated using capacitive sensors. A new technique for automatically sorting scrap non-ferrous metals uses a dual energy X-ray transmission sensor in conjunction with an electromagnetic sensor is introduced in [65]. It is presented how a sorting system with both sensors can replace

(a) (b)

Fig. 7 **a** Vehicle for plastic waste segregation [35] **b** Training batch for YOLOv7 algorithm [36]

traditional ferro-silicon-based dense media systems with a completely dry process.

In [66] an indirect sorting process that employs a camera sensor to recognise features and a mechanical separating process is introduced which consists of a compressed air nozzle, with the target particles being blown out of the mainstream. The positions, colours, sizes and shapes of each waste particle can be estimated and used as sorting criteria identified by the sensor. In [67] various methods to segregate plastics are mentioned including wet and dry separating techniques. There are now three primary options for managing plastic wastes: Mechanical recycling, feedstock recycling and chemical recycling.

This type of system is capable of expelling from the main waste stream at various distances the detected waste particles with particle sizes greater than 6 mm. Figure 9 depicts the basic operating concept of the entire sorting mechanism. In Fig. 10 authors created a triboelectric cyclone separator which has been used to successfully separate plastics in the lab. When considering the experimental findings, the recovery and purity of each product were both more than 75%.

2.2.2 Waste sorting using robotic systems

In recent years, there have been significant developments in intelligent robot technology for waste sorting. Various studies have explored the use of robots with sensors, computer vision, and robotic arms to detect and sort different types of waste. For instance, in [22], authors developed a robot vehicle and arm that use IR, metal, ultrasonic, and moisture sensors to separate dry and moist trash. In [23], a robot arm was designed to sort plastic, organic, and metallic waste, with the system controlled remotely via a mobile Java software. Similarly [35], presented a design of a robotic vehicle that uses computer vision to sort plastic waste into seven categories, while [25] introduced an integrated system consisting of an electronic robotic arm with sensors for sorting waste into biodegradable and non-biodegradable categories. Furthermore, [68] developed a modular cartesian robot for sorting cardboard, and [69] designed a robotic arm with five servomotors and a mechanical gripper to sort multi-materials. In [70], a robot arm equipped with a two-finger gripper and a location and grasping AI system was used to sort opaque plastic containers, paperboard boxes, transparent plastic bottles, cans, and plastic bottles.

In [71] a 6-dof robotic arm for recycling and sorting waste is depicted in Fig. 11a. To help the robot handle complex site scenarios, it employs SLAM technology and the instance segmentation method. In [72] a 6 DOF robot arm manipulator is designed for autonomous tomato harvesting system. The gripping mechanism for tomato harvesting is shown in Fig. 11b.

In [73] a pilot robotic cell is created and evaluated against industry standards for a variety of sorting activities. The CloPeMa dual-arm robot and pinch-like two finger grippers with compliance support serve as the foundation of

Table 1 Waste material detection using various sensors and algorithms

Papers studied	Materials sorted	Algorithm used	Accuracy	Drawbacks
[41]	PET plastic, plastic bottles, metal, glass	ResNet-50 (CNN model of 50 layers)	Detection model classification accuracy: 98.53% IoT-based sorting machine accuracy: 89.77%	The collection of photos should be thought of as offering both an empty bottle and a bottle cap in order to create a strong classifier
[35]	Types of plastic: PET, HDP, PVC, LDPE, PP, PS, other	Self-defined CNN model with 15 layers	Average accuracy of 87%	Accuracy of the network is lower than the papers referred
[42]	Glass, metal, plastic, paper	VGG-16, AlexNet, KNN, SVM, RF	VGG-16: 93.0% AlexNet: 91.0% SVM: 80.0% RF: 85.0% KNN: 88.0%	The least accurate and most challenging material to categorize is glass
[43]	Opaque and clear plastic bottle, opaque plastic container, cardboard box, drink can	Mask-RCNN	Max validation accuracy: 89.6% Max test accuracy: 55.6%	Because of the shadows and reflections of objects they may be classified inaccurately
[44]	Glass, fabric, metal, plastic and paper	YOLOv4	92.23%	The majority of waste collections utilized are single waste photos which are insufficient to meet needs in real life where various types and amounts of waste are combined
[27]	Bio, glass, metal, plastic, non-recyclable, other, paper, and unknown	EfficientDet-D2, EfficientNet-B2	70% in waste detection, 75% classification accuracy	It was not examined that how detection performed in various different environments
[17]	Construction waste (Cotton gloves, Wood block, Small ferrous, Plastic pipe, Bamboo, Corrugated Paper, Steel Bar)	Mask R-CNN	Mean Average Precision (mAP) is maximum in low Light–dark contrast i.e., 71.9% mAP for box detection and segmentation approaches 0.66 and 0.68, respectively	It is challenging for the LiDAR to identify a location that has been seen before with only a few LiDAR scans during the initial localization step
[34]	Cardboard, Plastic, Glass, Paper, Metal, and Trash	Faster R-CNN	91%	The model's prediction was inconsistent, and it occasionally failed to correctly identify waste things in an image with multiple objects
[45]	Garbage (tested only on bottles)	pre-trained Mobile Net (type of CNN)	90%	The current prototype can only pick up 100–200 g of trash
[46]	Glass, paper, cardboard, plastic, metal, and trash. (Digestible and indigestible waste)	CNN	95.3125%	The huge range of differences between various objects is the current issue this trained model is facing. Glasses come in a variety of thicknesses and colours. A human finds it difficult to categorise from such phenomena

Table 1 (continued)

Papers studied	Materials sorted	Algorithm used	Accuracy	Drawbacks
[47]	Plastic, paper and metal	SVM, CNN	SVM- 94.8% CNN- 83%	The study's limitation was the small number of photos in the training set
[48]	Used button cell batteries	Strict Convolutional, Image Splitting, Deep Scaling	80% and above	The robot functions as expected, but a communication interface must be established in order to manage and test the taping station for the lithium batteries and transmit data from the vision system to the robot
[49]	Nuclear waste simulants	DCNN	Around 90%	The detection is likely to fail when the background is complex or unknown. This is because the objectness localization needs much more data to generalize, and 2D based detection is more sensitive to variance in the background
[50]	Random grabbing objects	LSTM	Above 90%	The tactile sequence is typically responsible for the training error. The sample length chosen during training will always result in missing data in the data set because the length is not consistent
[51]	Paper, plastic, metal, and glass	SVM	78.3%	The detector network's downside is that it could occasionally be unable to find the target item; in this situation, the class-agnostic affordance map is actually preferable
[52]	Cardboard, glass, metal, paper, plastic, and organic waste	YOLOv3	94.99%	The trash image recognition process is extremely sophisticated, object detected may be classified into wrong class due to similarity in its appearance
[53]	Glass, paper, plastic, metal, and trash	Densenet121, InceptionResnetV2, MobileNet, Xception, DenseNet169	Densenet121: 95%, MobileNet: 84%, DenseNet169: 95%, InceptionResnetV2: 94%	Fewer TrashNet dataset samples, which results in lower accuracy
[19]	Shoes, cutting board, can, bottle, battery, clothes, cigarette, ointment, wash supplies, power bank, pillow, pot, plastic hanger, tea residue, and plush toy, plastic toy, courier bag	YOLOX	mAP: 84.67%	Poor generalisation of the training model was caused by the low number of photos in TrashNet. Also, they are all single object images

Table 1 (continued)

Papers studied	Materials sorted	Algorithm used	Accuracy	Drawbacks
[20]	Hazardous garbage, kitchen garbage, and other garbage	YOLOv4	64%	It is not ideal to be used with embedded devices
[36]	Chips packets, plastic bottles, polythene, and photographs	YOLOv7	f-measurement: 95.9%	The dataset used in the study is relatively small and limited to four categories of garbage. The model's performance needs to be tested on a larger dataset with more categories of garbage. Future research could explore the use of multimodal features for garbage classification
[39]	Trash, plastic waste, and cars	YOLOv3	–	-
[40]	Peels, bottles, cigarettes, glass, tiles, batteries	YOLOv7	95.4%	Only 2400 images in dataset were used which is very less for detecting household waste with accuracy
[19]	The dataset consists of 12 categories of trash, including plastic bottles, cans, paper, and glass	YOLOX	94.5%	Does not provide insights into the real-world implementation of the model or its performance under different environmental conditions
[20]	Consisting of six categories: paper, plastic, metal, glass, cardboard, and trash	Includes several modifications to the YOLOv4 architecture, such as adding SPP (Spatial Pyramid Pooling) and SAM (Spatial Attention Mechanism) modules	95.16%	The proposed model achieved high accuracy on the garbage classification dataset, the authors did not investigate the generalizability of the model to other datasets or real-world scenarios. Additionally, the authors did not provide a comprehensive analysis of the proposed modifications and their impact on the model's performance
[39]	–	YOLOv3	–	Does not provide a detailed analysis of the accuracy of the YOLOv3 model used
[54]	Metal, paper, glass waste categories, including the polyethylene terephthalate (PET) waste	SVM	96.5%	The dataset used in the study is relatively small, comprising only 2400 images in total with only 500 images for each class

Table 1 (continued)

Papers studied	Materials sorted	Algorithm used	Accuracy	Drawbacks
[55]	Plastic, paper, cardboard, metals	Convolutional Neural Network (CNN)	76%	Less accuracy is caused when classifying the metal from other categories. The dataset used in the study is relatively small, comprising only 2,410 images, which may not be representative of the various waste items found in real-world scenarios. Also, the paper does not provide implementation details, such as the software used, making it difficult to reproduce the results or implement the proposed system in practical applications
[56]	Plastic Bottles	Region Proposal Generation (RPN) and the VGG-16 model	-	Segregate only plastic. Output reliant on lighting
[57]	Recyclable Paper	KNN	93%	Only one class- paper is detected
[58]	Glass, plastic, metal, trash	VGG-16, Fast R-CNN, MobileNetV2	VGG16: 96.1% Fast RCNN: 88% MobileNet V2: 85%	The dataset—TrashNet used in the study is small, with only 2527 images in total
[59]	Recyclables, kitchen waste, hazardous waste, other garbage	WasNet-Lightweight neural network	ImageNet: 64.5% Garbage Classification: 82.5%, TrashNet: 96.10%	Results and execution are not dependable. The majority of the trash is thrown together, in real life. In this situation, the solution to the issue of intelligent garbage sorting and recycling is crucial. The classes made despite having broader dataset, are not good for classification of individual materials
[60]	Organic, Non-organic waste	SIFT (Scale invariant Feature Transform) algorithm	89.9%	The dataset is very small and classes are too broader for waste classification
[61]	Recyclable waste paper	DNA computing algorithm (Fast-R CNN)	91%	Only one class – paper is detected

the experimental testbed made up of two separate, industrial manipulators with six degrees of freedom. In [74], a robotic sorting system is presented, consisting of a vision system, a 5 m long conveyor, a SCARA robot, and a pneumatic gripper. The system recognizes object's sizes and locations on the conveyor using machine vision. Paper [75] introduces a method for dividing a warehouse into two pick zones using a Non-dominated Sorting Genetic Algorithm II, minimizing human workload. A robot picker is used in one zone while human pickers are used in the other to organize products. Study [76] describes a robot for recycling C&D garbage that uses simultaneous localization and mapping to provide real-time navigation. In [77], a novel parallel robot design is introduced for quick and energy-efficient waste sorting. The platform can be customized at the end of the parallel construction to allow the clamp to move, and the gripper is directly controlled by four actuators on the manipulator's base. In [78], a robot is designed to categorize plastic waste into seven different groups based on camera images. The vehicle

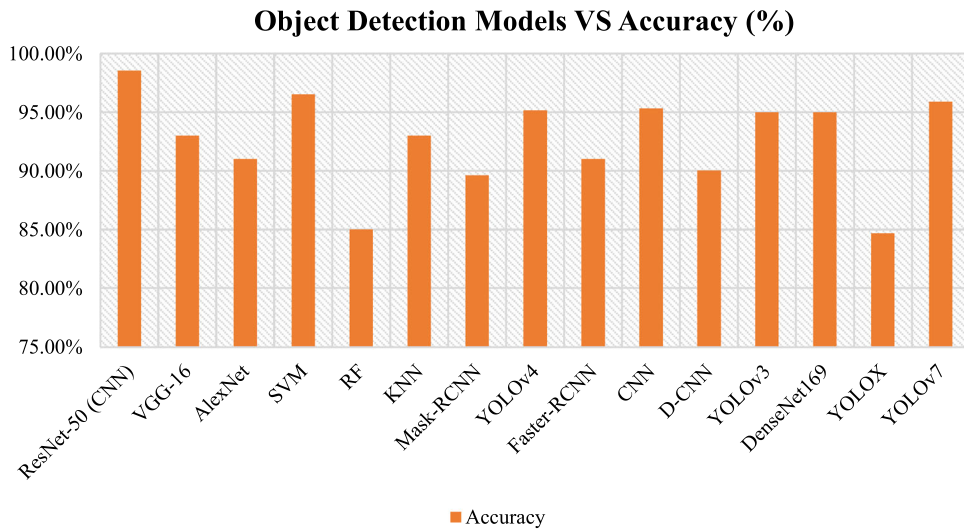


Fig. 8 Object detection models versus their accuracy

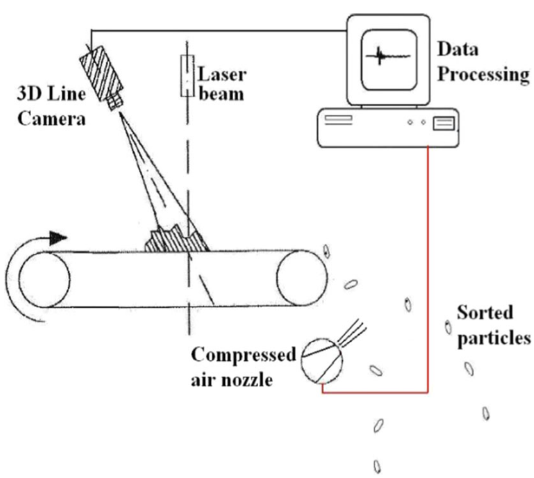


Fig. 9 Principle of the sorting system [66]

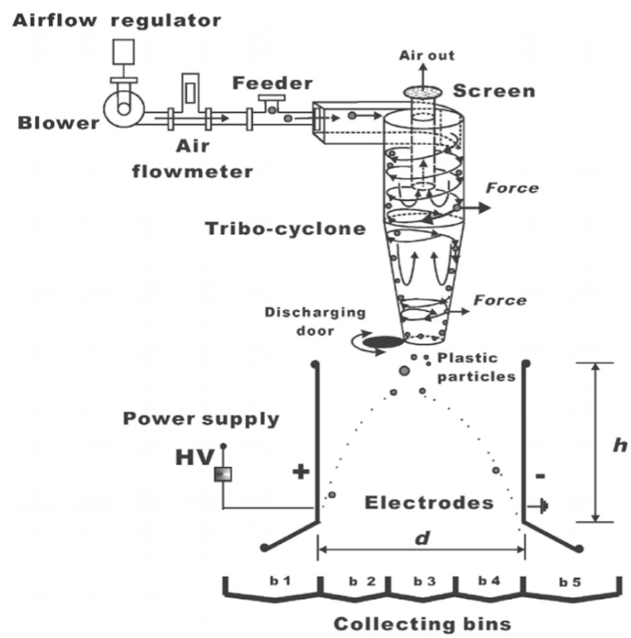


Fig. 10 Schematic design of triboelectric cyclone separator [67]

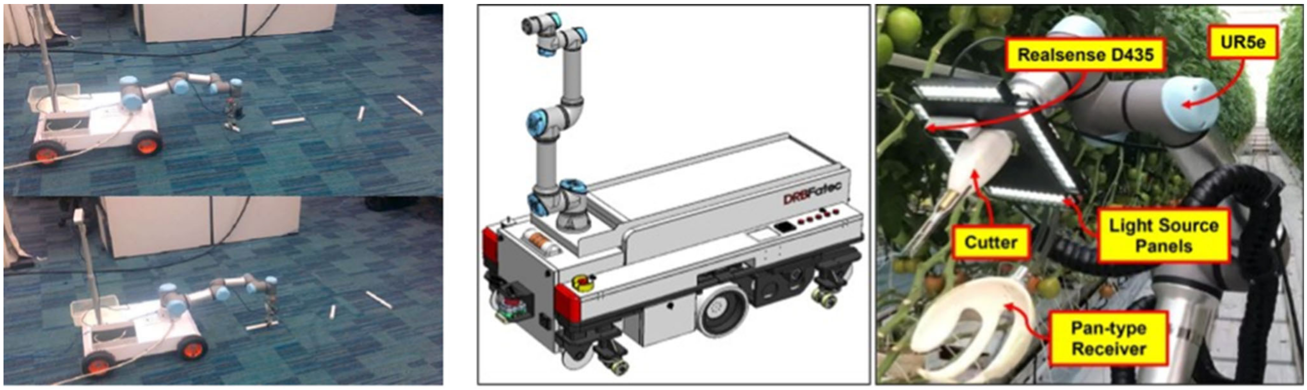
employs artificial intelligence and computer vision techniques for garbage recognition. In [79], a system is designed consisting of a conveyor belt, two robot arms controlled independently using Arduino microcontrollers, a computer vision system, and a Raspberry Pi as the master controller. The end effector is a vacuum suction gripper, and the robot arm has a payload of 500 g. In [80], an autonomous robotic arm system is presented that uses Internet of Things (IoT) devices to classify and sort various items. The PhantomX Reactor Robotic Arm was utilized in this study.

The Flowchart shown in Fig. 12 demonstrates the most common process followed while sorting waste using robotic mechanisms.

Overall, the recent research papers demonstrate that waste sorting using robotic systems has the potential to revolutionize the waste management industry and contribute to a more sustainable future. The use of robotic systems for waste sorting can significantly improve waste management efficiency, reduce human involvement, and minimize the risk of occupational hazards. The robotic systems are highly accurate, efficient, and can handle a wide range of waste materials. However, further research is needed to optimize the performance and cost-effectiveness of these systems to make them more practical for wider range of waste materials and operating in different environments.

2.2.3 Robotic grippers for segregation

The development of robots is influenced by their capacity to grasp and handle objects. Advances in gripper technology



(a) (b)

Fig. 11 **a** Orientation of gripper for picking object [71] **b** Robot arm and gripping mechanism for tomato harvesting [72]

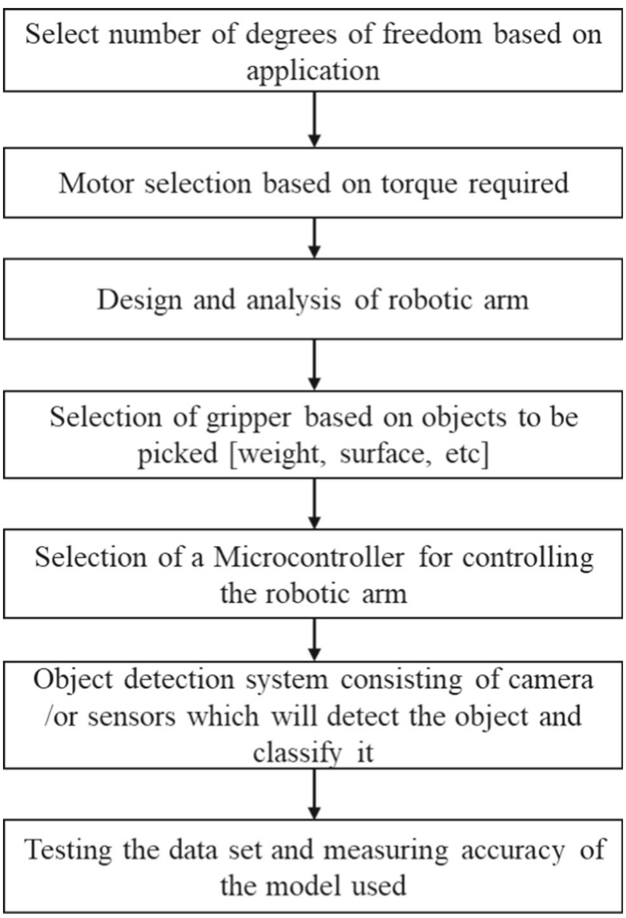


Fig. 12 Process of sorting waste using Robotic Arm

allow manufacturers to pick, place, and pack products with greater accuracy, performance, and productivity by leveraging end-effector tooling. Similarly, the design and selection of the gripper plays an important role in sorting various waste materials of different shapes and size. This is a major challenge faced in robotic waste sorting as a single gripper cannot fulfil the task of picking and placing waste made of different material, shape, size, orientation, etc.

In [81], the paper discusses the state-of-the-art robotic grippers, the different types of robotic grippers and discuss the advantages and limitations of each type of gripper and the different materials used in their construction. The number of DOF, actuation system, design strategy, and geometry of the objects being grasped are all used to categorise grippers in the paper [82]. It is possible to learn which gripper design has the most capabilities by comparing the benefits and drawbacks of each categorization criterion.

Grippers can be classified into two categories: soft and rigid grippers. Soft grippers are made of flexible materials and are capable of grasping delicate objects. Rigid grippers are made of hard materials and are capable of grasping heavier objects [81]. In [83], authors have designed a two-jaw gripper with rubber pads, using rack and pinion mechanism for prototyping a collaborative robot arm which has a payload of 1.5 kg. This design and application can be modified to sort heavy wastes along with computer vision.

In [84] the study sets a new standard for 3D manufacturing soft actuators as shown in Fig. 13a. These three fabrication techniques—casting, multi-material polyjet printing, and RLP—are used to create soft actuators, and their properties are displayed. In [85], to increase the gripping flexibility of robotic manipulators, a trimodal adaptive end-effector is developed. It can use effective grasping strategies depending on the object's size and porosity. Study also focuses at deploying gripping modes that are efficient for holding onto the recyclable object, even though its mechanical design permits the three gripping modes to deployed individually or in conjunction with one another as shown in Fig. 13b. From the studies it can be seen that more research can be done in implementing grippers with new design and innovations to facilitate the pick and place operation of multiple classes of waste with varying dimensions.

(a) (b)

Fig. 13 **a** Printed gripper- bending and gripping [84] **b** A single gripper with multiple gripping mechanisms [85]

3 Challenges

Some of the major challenges faced as well as scope for future research in the implementation of robots in waste sorting are discussed below:

1. Datasets are not large enough for accurate prediction of waste. The datasets used in the various studies are very small when it comes to real-life implementation in waste detection. This affects overall accuracy of the detection model.
2. Improving the dataset. The number of classes in waste detection studies are very small where only few items like plastic bottles, cardboard, can bottles are detected whereas, the actual recyclable waste materials are large in number and differ from one another. Thus, definition of large datasets along with broader classes is crucial for efficient and accurate waste sorting in real-time. The existing research studies analyzed are overwhelmed by the shortage or incompleteness of solid waste data [26].
3. Instead of using one arm for multiple trash-objects sorting, many sub-systems of robot arm and object detection models specific to objects of single materials sorted can be implemented for large-scale trash sorting. For example, for plastic sorting multiple plastic items like straws, bags, wrappers, bottles, etc., can be sorted with a robot dedicated only to sorting plastic with maximum accuracy and efficiency; similarly individual robots can be used for different recyclable materials.
4. Plants for sorting with systems of conveyors and robotic arms can be implemented for large-scale sorting and recycling of waste. The collection of trash and transport of the garbage to the plant will be a major challenge economically.
5. Due to the different types of wastes, the robot system may require maintenance on a regular basis. This can increase its implementation costs.
6. Since the size, shape and weight of the trash varies, selecting single type of gripper for sorting is not efficient [82].
7. The robotic system must be able to identify the categories, orientations, and states of various trash objects to move them according to the category that needs to be sorted [86].
8. The focus of current research on applying Industry 4.0 technologies to specific waste management systems, lacks the consistency required to fully utilize technologies like interconnectivity, cloud computing, big data, etc. on a greater scale [87].
9. A fully functioning waste management system consists of many subsystems like detection algorithms, sensors, actuators, power management system, conveyors, etc. They have not been fully commercialized and hence expect further advancements to make the system efficient and sustainable.
10. Development and installation of a cost effective and robust robotic system requires high investment and may force the society to reconsider using manual sorting, based on total expenditure.

4 Conclusions

The paper gives an overview of the current scenario of working and development of robots in waste sorting in the future. As seen in the literature review, despite of the advantages, there are several challenges faced in implementing autonomous robots for waste sorting with current technologies as well as existing object detection models. More focus can be given in building algorithms and models with maximum detection accuracy as well as robots with greater sorting efficiency.

In this study, 32 papers are compared in a tabular form, including the accuracy of the model, the classes identified in the object detection model, and the ML/DL models used in each paper. It was found that there are not many papers available related to robotic waste sorting, so our paper provides a better review and comparison of the various studies. ResNet-50 has the highest accuracy of 98.53% [41] and thus more study can be done to improve accuracy of that model. Also, other models like SVM, YOLOv4, YOLOv7 have accuracies greater than 95% which can be further improvised with better training and datasets.

Object detection has been found to be a more effective and precise method for segregating waste with various materials, shapes, and sizes than sensors that rely on factors such as material, colour, odour, and moisture. To achieve the desired robotic systems for waste sorting, there are three main challenges that need thorough research in the future- 1) Object Detection model must be tested and trained well with a dataset covering all the classes of waste to improve the overall performance of waste detection. 2) A Single End-effector as shown in [85] with multiple gripping options can be used for waste sorting as it can pick and place variable objects. But the manufacturing process and cost of manufacturing such grippers could pose a major drawback. 3) Implementing complete robotic waste sorting system on a larger scale requires huge investment and maintenance and hence more research is needed. Research for developing new sorting mechanisms and new grippers can be done as trash material has ambiguous shape and using traditional grippers is not efficient. Also, there is a need to build a dataset with as many waste images as possible along with different orientations such that almost no trash items pass undetected. A waste sorting system with many robot arms and good waste sorting gripper, a good conveyor system for movement of waste and a waste detection system can be worked on in the future.

From this review, we can see a greater scope in robotic waste sorting taking over traditional waste sorting systems. To implement this on a larger scale, research in collaborating robot arms along with well-trained object detection models is needed. It is seen that with time, research is needed for both increasing detection accuracy as well as efficiency of robot arms. However, the problems facing the waste-sorting industry exceed the capabilities of any single existing robot. To tackle the problems facing the recycling industry is a massive undertaking. Due to the broad scope of the problem and the industry, more research and development needs to be undertaken before any solutions will be widely implemented. Further research and new innovations are necessary to improve current technologies to make them more accurate and efficient.

Acknowledgements Not available.

Author contributions The first draft of the manuscript was written by AS, CA and AP. AS, GA and SK performed the conceptualization of the research idea and reviewed the edited manuscript. All authors have made a substantial contribution to the manuscript. All authors read and approved the final manuscript.

Funding No funding was received for conducting this study.

Availability of data and materials Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Competing interests The authors declare that they have no competing interests.

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