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Garbage Collection and Sorting: A Review

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Abstract—Urbanization and population growth are causing 70% garbage creation annually. Due to this, the modern world faces lots of challenges. Being one among them, Waste Management has become a matter of great concern due to the lack of a proper disposal system. Well organized garbage management can contribute to the country's health and wealth. In this order, we propose a smart solution which we termed as Automatic Waste Sorter. In this project, our goal is to provide waste segregation and reduce human involvement. When sorting and moving waste, extreme care must be taken to ensure the least possible risk to the environment and public health. Proper segregation of waste material makes recycling more feasible and effective. A deep learning algorithm embedded into a microprocessor with several sensors attached to it, can assist the proposed autonomous device in identifying the living organisms and spare their lives during garbage collection. A special mechanism can then be used to place the dissolvable and non-dissolvable garbage separately. The method has the potential to increase recycling rates, decrease pollution, and conserve resources. The proposed autonomous device constituted with IOT, deep learning and machine learning can significantly improve the environment.

Index Terms—Garbage, Robotic Arm, Deep Learning, Sensors, Mask-RCNN, Mobile Net

I. Introduction

Plastic has integrated into our daily life. Plastic may be used for a variety of things because it is lightweight and quite sturdy. The transportation sector makes extensive use of plastic. Plastics are also used to make a lot of sporting items since they are lightweight, waterproof, and durable. Syringes and other popular medical equipment are made of plastic, yet this material is hazardous to both human and animal health.

A plastic bottle may not decompose for 450 years or longer. Plastic bottles are now a significant source of municipal garbage. Polyethylene terephthalate (PET) plastic, which is used to make water bottles, degrades over time into tiny plastic fragments. These fragments are either imbedded in the land and remain there for years, or they are carried into the seas by running water sources. Such plastic is ultimately consumed by land and sea animals, making them ill. The hazardous effects of eating such animals can be harmful to human health. This highlights how crucial it is to recycle plastic.

Researchers have proposed many techniques for the separation of different materials or types of waste. One such method, referred to as" tribostatic separation," employs contact electrification to sort plastic materials [1]. The" hydro cyclone" technique leverages centrifugal force to segregate objects based on their density, while" jigging" relies on the interplay of buoyancy, gravity, and acceleration for density-based separation [2]. The" disc screen" method aids in size-based sorting, and" eddy current-based separators" are employed to distinguish non-ferrous metals from non-conductive materials [3]." Magnetic density separation" is utilized to categorize various polymeric materials by adjusting the density of a magnetic fluid, leading to the differential floating of polymeric materials with varying densities [4]. The" froth flotation technique" exploits the hydrophobic nature of plastic to separate it from the waste stream [5].

Additionally, various vision-based techniques have been harnessed for the separation of different waste types through methods such as feature matching and X-ray-based sorting. However, it is important to note that these techniques are specific to particular waste categories. Consequently, it is recommended to employ deep learning-based classifiers, as they possess the ability to classify a broad spectrum of waste types, contingent upon the availability of adequately trained datasets. Notably, deep neural network (DNN) based classifiers exhibit high accuracy and expeditious results, rendering them more efficient in this context.

Researchers worldwide have made significant contributions to the enhancement of municipal waste management systems. These contributions encompass the utilization of eddy current technology to segregate ferrous and non-ferrous metallic waste, the deployment of trommel systems for mechanical rotary sorting based on size, the design of dry and wet waste separators, the implementation of waste-sorting robots, as well as vision-based and inductive sensor array-based waste sorting methods. These systems have been conceptualized and subjected to rigorous testing for a broad range of waste materials, including recyclable paper, plastic, glass bottles, non-ferrous metals, metallic waste, and general municipal waste.

In a report from March 2021 (see figure 1), the Ministry of Housing Urban Affairs stated that the country generates 26,000 tonnes per day (tpd) of plastic waste. Of this amount, 9,400 tpd remains uncollected, leading to pollution in streams and groundwater resources. It's important to note that these plastic waste figures pertain to the entire country, primarily focusing on urban India, with no separate data available for rural areas.

Naveen Arora, who serves as the head of the Department of Environmental Sciences at Babasaheb Bhimrao Ambedkar University in Lucknow, highlighted significant gaps in the official reporting of waste generated in rural India. He explained that the government's estimates and data on plastic waste generation often overlook most small factories in rural regions

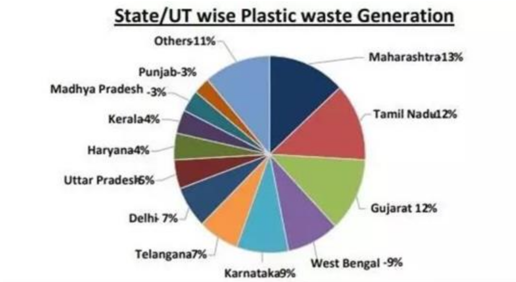

Fig. 1. State Wise Plastic Generation

that produce items such as polythene, snack wrappers, and plastic bags. The plastic produced by these rural units, when improperly disposed of, ends up contaminating agricultural fields and small water bodies, causing environmental damage.

The Central Pollution Control Board (CPCB), responsible for maintaining records on waste generation and management in the country, does not maintain separate data for urban and rural India. Instead, the data is aggregated on a state-wise basis.

According to the Annual Report for 2019-20 on the Implementation of Plastic Waste Management Rules, 2016, published by the CPCB, Maharashtra is the leading contributor to plastic waste in India, accounting for 13 percent of the total, followed by Tamil Nadu and Gujarat, both tied at second place with 12 percent (refer to figure 1).

In the face of escalating environmental concerns and the alarming projection that global waste production could surge by 70% annually [6], addressing waste management has assumed paramount importance. Current waste disposal methods, primarily mixed landfill and mixed incineration, are deemed inadequate to cope with the impending deluge of garbage [6]. Consequently, the need for innovative approaches to waste management has never been more pressing. Over the past few years, a considerable emphasis has been placed on the research and development of garbage disposal technologies, particularly in the field of garbage sorting. Effective garbage classification, a vital facet of recycling economies, offers a promising avenue for sustainable development [7]. Various strategies, such as garbage classification policies and advanced technologies, have been explored to optimize waste management systems [8]. In this context, the integration of artificial intelligence (AI) and machine learning (ML) technologies into waste management has gained traction. Researchers worldwide have endeavoured to harness the potential of AI-driven systems for efficient garbage sorting, ranging from machine arms and sorting lines to deep learning algorithms [9]. These endeavours have yielded a spectrum of solutions, each with its strengths and limitations, from object recognition systems based on neural networks [9] to intelligent waste bins [10].

Furthermore, the convergence of the Internet of Things (IoT) and deep learning models has paved the way for the development of smart waste management systems. IoT-based sensors and devices, coupled with AI-powered garbage detection and categorization, offer novel approaches to optimize waste collection, reduce environmental pollution, and enhance resource utilization [7]. This review paper amalgamates and synthesizes the insights and innovations presented in distinct research papers, each offering unique perspectives on the challenges and solutions in waste management. These papers delve into topics such as deep learning-based garbage detection, agile waste-sorting robotics, IoT integration for waste monitoring, and lightweight neural networks for garbage classification.

The paper's summary is structured as follows. The related literature is discussed in Section 2, and the date-set and approach are explained in Section 3. The results and discussion are presented in Section 4, and the conclusion is presented in Section 5.

II. RELATEDWORK

The authors' study, Optimizing Convolutional Neural Networks for Resource-Constrained Environments [1], was carried out. Computing cost has steadily elevated to the status of one of the most important network configuration factors since the CNN model's creation. We should additionally take into account the hardware platform's operating time for apps with constrained resources. Certain vast and sophisticated models, as well as some real-world mobile or embedded device settings, are difficult to apply. Consequently, there are two main directions for the optimization algorithm: designing and training the minor model directly, or compressing the complex model to achieve a little model. Then followed the SqueezeNet [16], ShuffleNet [17], and MobileNet [18], whose main objective is to reduce the size and enhance the speed of

Model	Parameters (Millions)	Top-1 Accuracy (%)	Top-5 Accuracy (%)
AlexNet	61	57.2	80.2
VGG-16	138	71.0	89.8
GoogleNet	4.9	68.8	88.9
ResNet-50	25.6	76.0	92.5
MobileNet	4.2	70.6	89.5

TABLE I
MODEL COMPARISON

Layer	Kernel Size / Stride	Output Size
Input	224 x 224 x 3	224 x 224 x 3
Conv dw	3 x 3 / 2	112 x 112 x 32
Conv dw	3 x 3 / 1	112 x 112 x 64
Conv dw	3 x 3 / 2	56 x 56 x 128
Conv dw	3 x 3 / 1	56 x 56 x 128
Conv dw	3 x 3 / 2	28 x 28 x 256
Conv dw	3 x 3 / 1	28 x 28 x 256
Conv dw	3 x 3 / 2	14 x 14 x 512
Conv dw	3 x 3 / 1	14 x 14 x 512
Conv dw	3 x 3 / 2	7 x 7 x 1024
Conv dw	3 x 3 / 1	7 x 7 x 1024
Average Pooling	Global	1 x 1 x 1024
Fully Connected		1000
Softmax		1000

the model while maintaining the performance of the model. MobileNet - The Lightweight Model Several well-known models of convolutional neural networks are AlexNet [19], VGG [20], GoogleNet [21], and ResNet [22]. Although a deeper network can produce higher accuracy, the price is a complex network model and plenty of calculations. Compared accuracy over ImageNet dataset and required parameters with prevalent models, the results of Table I are demonstrated to show the MobileNet's advantage characteristics. The results depicted that MobileNet has good performance in training lightweight CNN networks on mobile terminals or embedded equipment, and can also be deployed as a backbone network in the object detection system effectively. MobileNet is based on streamlined architecture that uses depth wise separable convolutions to establish lightweight deep neural networks. The general convolution operation is to directly use the convolution kernels with a size greater than or equal to three to fuse the feature map. The basic unit of MobileNet is depthwise separable convolution (DSC), which can be decomposed into two smaller operations: depthwise convolution and pointwise convolution. The deep convolution uses different convolution kernels for each input channel, that is, a convolution corresponds to an input channel. Through the deep convolution operation using the convolution kernels with the size of three, the output feature matrix channel equaling to the input feature matrix channel is obtained. As for pointwise convolution, it's an ordinary convolution involving a 1 × 1 convolution kernel. In general, for depthwise separable convolution, the first is to use depthwise convolution to convolve different input channels separately and then use the pointwise convolution to combine the above outputs. The overall effect is similar to a standard convolution, but it will greatly reduce the amount of calculation and the number of model parameters. Furthermore, we can illustrate the distinction between Depthwise Separable Convolution (DSC) and the regular convolution through a straightforward computation. Assuming that the size of the input feature matrix graph is Df × Df × M, and the size of the output feature graph is Df × Df × N, where M and N represent the number of channels, and Df denotes the width and height dimensions of both the input and output feature graphs. In the case of standard convolution, the size of the convolution kernel is Dk × Dk. Consequently, the computation volume for standard convolution is given by Dk × Dk × M × N × Df

× Df. For depthwise convolution, the computation amount is Dk × Dk × 1 × M × Df × Df. As for pointwise convolution, the computation amount is M × N × Df × Df. Hence, the key distinctions between DSC and standard convolution can be summarized as follows: DSC CNN = Dk × Dk × M × D f

× D f + M × N × D f × D f Dk × Dk × M × N × D f × D f

= 1 N + 1 D2 k. (1)

DSC CNN = Dk × Dk × M × D f × D f + M × N × D f × D f Dk × Dk × M × N × D f × D f = 1 N + 1 D2 k. (1)

As can be seen from (1), if the convolution kernel uses 3 × 3, DSC can reduce the calculation amount by about 9 times compared with the standard convolution. The architecture of MobileNet is a 3 × 3 standard convolution, and then the depth wise separable convolution is stacked behind, while some of the depth wise convolution down sampling by strides is 2. Besides, the feature is changed into 1 × 1 by using the average pooling, and the full connection layer is added according to the size of the predicted category, finally a SoftMax layer is formed. The specific architecture is shown in the following Table II, where Conv dw represents the depth wise convolution in the DSC operation.

B. Mask R-CNN – The Framework of Object Detection The Mask R-CNN network [11] was constructed byHe, Kaiming created the Mask R-CNN network [23], which won the COCO 2016 competition and significantly increased instance segmentation accuracy. The frameworks consist of three main stages: positioning, segmentation, and recognition. The enhancement primarily consists of three components: the addition of a paratactic FCN layer, the replacement of the ROI Pooling layer with the ROI Align layer, and the use of ResNet

TABLE II ARCHITECTURE OF MOBILENET

deep residual learning, which has a greater ability in feature expression and FPN network mining multi-scale information. ROI Align efficiently prevents the pixel bias mistake in ROI pooling and addresses the misalignment aligning issue by employing a bilinear interpolation approach when growing the feature map.It improves the performance of instance segmentation in spite of improving the accuracy of detection. The Mask R-CNN was utilized by Li Shipeng et al. as a framework for segmenting images of interest (ROI) in target recognition [24].Unstructured conditions like target occlusion, backdrop reflection, and object deformation are vastly inferior to this experiment. A two-stage deep learning approach was used by Cheng Junhua et al. [25] to lessen the interference of elements related to complicated backgrounds.The experiment therefore increased the complexity of background categorization accuracy.These tests demonstrate how popular the Mask RCNN has been in picture segmentation recently; this research likewise uses it. Deep learning-based objection detection algorithms can currently be broadly classified into two categories, which correspond with the advances of deep learning. The first is a two-stage detection technique, the main idea of which is to use the conventional window-sliding detection approach to extract candidate regions as alternatives. The CNN network computes each candidate region's characteristics and applies nonlinear classifiers, like the R-CN N, to make a determination [26].YOLO is one example of a one-stage detection technique that uses a model algorithm to determine the category and location of an input image, and then delivers those results directly [27] [12]. After creating a mask image of the ripe fruit using Mask R-CNN, Yang Yu et al. were able to identify the fruit at the strawberries picking location, improving the performance of the collection robot in strawberry fruit Trials have demonstrated how well this approach works to increase robustness and uniformity in unstructured contexts, particularly when it comes to hidden and overlaying those fruits under various lighting conditions. Mask R-CNN network structure with excellent accuracy in detecting in this study is appropriate for our scenario where the target, complicated backdrop, and need for high-resolution image has a little amount of information. Owing to the enhancement, each ROI's loss equation is modified using formula (2), and ROI aligns

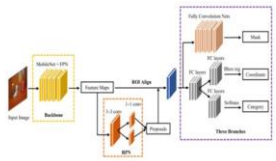

Fig. 2. MobileNet as Base CN in Mask RCNN

with the output of K × m × m dimensions, where k is the number of categories.The method makes advantage of the loss function as L mask (Cls k) = Sigmoid (Cls k), using a per-pixel sigmoid. By using a pixel-by-pixel Sigmoid calculation, the average binary cross-entropy loss is determined. The output of k-1 masks in L mask is only defined on the k-th mask for a ROI of class k in GT since it does not contribute to the overall output loss. The approach enables the network to create a mask for every class by establishing a L mask, hence preventing rivalry between classes and based on the class label anticipated by the categorization branches, choose the result mask.

L = Lcls + Lbox + Lmask. (2)

C.MobileNet as a Base Network of Improved Mask RCNN

Considerably, the best option for this experiment is the Mobile Net-based Improved Mask R-CNN. The present study proposes an efficient region extraction method based on the Mask R-CNN target detection framework. According to the accuracy premise, this study suggests using Mobile Net as the feature extraction backbone network in order to guarantee the overall framework's lightweight. Simultaneously, the unique aspect of FPN in our work is its independent prediction at several feature layers. The multi-scale object detection problems can be effectively solved by FPN in the Mask R-CNN network architecture. Without significantly raising the estimated quantity of the original model, the detection performance of small objects, like button batteries, can be significantly enhanced by making straightforward changes to the network connection. The Mobile Net is deployed as an effective base network in the MASK R-CNN object detection model as shown in Fig. 2.

A substantial amount of labeled data is needed to improve supervised learning efficiency and accomplish garbage identification in a complex background. By utilizing the similarities between tasks, data, or models, transfer learning [29] is able to extract useful knowledge from data in related disciplines. To address cross-domain learning issues, the model obtained in the previous discipline is incorporated into the new field's learning procedure [30]. Transfer learning serves the dual purposes of lowering model training costs and achieving the goal of convolutional neural network adaptation to small sample data. Because transfer learning enables the model to learn from many kinds of data, it is more adept at identifying the internal relationships within the issue so that the issue can be solved. It can enhance identification accuracy and general ability and successfully prevent overfitting when compared to typical handwork characteristics. Consequently, the primary focus of this paper is on feature extraction using the input layer and convolution pool division layer of the model trained using source data. Each convolutional layer's parameters are kept in the trained convolutional neural network model. Simply said, the final fully connected layer has been replaced. The output layer's model is modified to suit the purpose of classifying and recognizing rubbish in a particular scenario.

waste management and garbage collection, several approaches have been explored to improve efficiency and reduce costs. One approach involves the use of advanced technologies and the internet to streamline waste collection processes, as discussed in [2]. However, this method faces challenges in some countries, such as the need for waste collectors to arrive at specific locations on time and the lack of sorting and recycling at the source. Fixed waste bins can also lead to issues like overfilling and unsanitary conditions. Various sensor-based solutions have been proposed, such as ultrasonic sensors, IoT, and wireless sensors, which can alert municipal authorities when garbage bins are full, as presented in references [4], [5], [13], and [14]. These systems help in segregating wet and dry waste, which is crucial for appropriate disposal methods. Additionally, some smart garbage cans are equipped with sensors to measure garbage weight and level, optimizing collection routes and schedules [7], [10]. However, these sensor-based solutions often have limitations in terms of recyclable waste types, accuracy, and complexity.

In recent years, there has been a shift towards using neural network methods, particularly convolutional neural networks (CNNs), for garbage classification. [9] compared various CNN architectures and achieved high accuracy in classifying different types of garbage. [15] employed SoftMax and Support Vector Machines (SVM) as classifiers, along with transfer learning, to achieve even higher accuracy on the TrashNet dataset. However, these CNN models can be computationally expensive and require substantial hardware resources.

Another aspect of waste management is monitoring the fill level of garbage bins, as discussed in [1]. Various sensors, including infrared, ultrasonic, and moisture sensors, have been used to detect the amount of garbage in bins. These sensors can communicate with central systems or web servers to alert authorities when bins are full. Low Power Wide Area Network (LPWAN) technologies like LoRa have been explored for long-distance data transmission, making it easier to monitor multiple bins across a city [16]. Cloud-based systems have also been developed to track waste bin conditions and predict future requirements, improving the overall efficiency of waste collection [17].

Additionally, research has focused on waste sorting and classification using deep learning methods. Reference [?] introduced WasteNet, a CNN model that achieved high accuracy in waste classification on the TrashNet dataset. Genetic algorithms were applied to optimize the model further. TrashNet, a dataset with various waste categories, has been made available to the public [?], providing a valuable resource for training waste classification models. Other studies have combined deep learning with object detection techniques to improve waste sorting accuracy [18], [?]. These approaches aim to automate the sorting process, reducing costs and simplifying recycling.

III. Methodologies

In this paper [6] Robotic Training Dataset Collection for Waste Sorting, the authors propose a methodology for collecting a training dataset for waste sorting using robotics.the fig.3: shows the algorithm which they have used. They employ a small hand-eye robot arm equipped with an RGB camera to capture images of target objects from various viewpoints. To extract object regions while considering outline blur, alpha matting is applied using large-kernel matting. Scaling of object images is performed to ensure consistency in appearance due to varying distances between the camera and the object. Additionally, color matching techniques, such as histogram matching, are used to reduce differences in illumination between the collected images. These methods help create a highquality training dataset for waste sorting robots.

[8] Smart Waste Management System Using CNN This

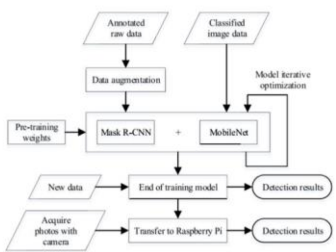

Fig. 3. Algorithm flowchart of RCNN

paper outlines a smart waste management system that employs Convolutional Neural Networks (CNNs) for real-time object detection and waste classification. The system's design includes a waste bin with compartments for different types of waste and utilizes TensorFlow Lite with the SSD MobileNetV2 Quantized 300x300 model for object detection. The dataset used for training is obtained from free sources and augmented through techniques like image shifts, flips, brightness changes, zoom, and rotations. Training the object detection model involves optimizing hyperparameters such as the learning rate. The chosen model and architecture, along with hardware components like Raspberry Pi and sensors, enable efficient waste classification and categorization within the bin.

[1] Data Collection and Analysis for Garbage Classification This paper focuses on the data aspects of garbage classification. It describes the collection of a comprehensive dataset comprising 30 categories of garbage for classification. The authors conduct data analysis, likely involving exploratory data analysis (EDA) techniques, to gain insights into the dataset's characteristics. Data enhancement techniques are employed to preprocess or improve the dataset for machine learning purposes. While the paper does not provide specific

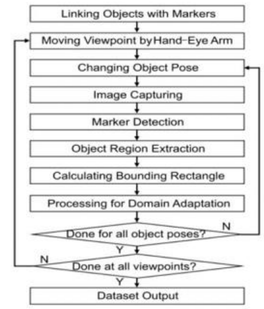

Fig. 4. flow of image dataset collection by robort [8]

formulas or algorithms, it emphasizes the importance of data collection, analysis, and enhancement to facilitate effective garbage classification. Experimental verification of machine learning models on this dataset is likely performed to assess the effectiveness of the data-related methodologies.[4] Data Analysis The authors conducted a comprehensive analysis of the dataset, examining data sample distribution, size distribution, and picture morphology. They observed that the data distribution among categories was uneven, which could lead to dataset skewing. To address this issue, they applied techniques like weighted loss functions to give more importance to underrepresented categories. The authors also noted variations in image aspect ratios and standardized input image sizes to 224x224. Data Enhancement: Data augmentation techniques were employed to improve model generalization. These techniques included horizontal and vertical flips, random panning, and more advanced methods like random erasing, Mixup, and Cutmix. These strategies help reduce overfitting and make the model more robust. Data Experiment: This section presents the results of experiments related to data modification and enhancement. The ResNet50 model was used for training on the Garbage Classification dataset. Different data enhancement strategies were tested, and the optimal combination was found to be horizontal and vertical rotation, translation, center image, Mixup, Cutmix, and random erasing. The experiments aimed to improve the model's performance. Deep Neural Networks: This section discusses the development of a lightweight neural network called WasNet for garbage collection management. The authors review the evolution of lightweight neural network architectures, including AlexNet, deep separable convolution, and ShuffleNet. They incorporate attention mechanisms like SE and CBAM into their network for improved performance. Experiments and Comparisons: WasNet's performance is compared with two other mainstream lightweight networks, ShuffleNet-V2 and MobileNet-V3-small, using the Garbage Classification dataset. Transfer learning from the ImageNet dataset is applied to enhance accuracy. The experiments demonstrate that WasNet outperforms other networks in terms of accuracy, parameter count, and computational complexity. System: The authors describe the system architecture, which includes smart trash cans equipped with Raspberry Pi for object identification and Android applications for real-time garbage classification. They also propose an adjustment mechanism to continually improve the model using user feedback. Project Architecture: The overall project architecture involves collecting data from smart trash cans and mobile applications, integrating and cleaning the data, and presenting it on a platform. This platform aids managers and decision-makers in making informed decisions regarding garbage collection and treatment.

IV. Results and Discussion

In these studies, significant progress was made in the field of garbage detection and waste management. Firstly, a comprehensive dataset comprising six common office and daily life waste items was meticulously constructed. Through the incorporation of data augmentation techniques, the dataset's quality and robustness were enhanced. Extensive experiments were conducted to evaluate various neural network models, ultimately selecting MobileNet as the optimal backbone network for garbage detection due to its remarkable efficiency and accuracy.

Fig. 5. flow of image dataset collection by robort [8]

Moreover, the deployment of the MobileNet-based Mask R-CNN model on a Raspberry Pi showcased its practicality and real-world applicability. Furthermore, another paper introduced innovative automation techniques for waste sorting and detection, effectively reducing the time and effort needed for dataset collection and training. Lastly, an integrated smart waste management system, combining computer vision and IoT technologies, enabled remote monitoring of waste bins' status and optimized waste collection strategies. These findings collectively underscore the potential of technology-driven approaches to address challenges in waste management and contribute to more sustainable practices in waste disposal and recycling. some of the tested and trained images shown in fig5.

V. Conclusion

This paper presents a novel robot system for cleaning the garbage automatically. Based on the powerful deep neural networks, the proposed robot can recognize and pick up the garbage without any human assistance. The development and implementation of autonomous vehicles for garbage collection and sorting hold great promise for addressing various challenges in waste management. These advanced technologies offer numerous benefits, including increased efficiency, reduced labour costs, enhanced safety, and improved environmental outcomes. Autonomous garbage collection vehicles can optimize route planning, minimize fuel consumption, and reduce traffic congestion by operating during off-peak hours.

Specifically, the use of deep learning integrated with machine vision is a novel contribution to the work discussed in the paper. The high accuracy achieved in the classification task demonstrates its potential for practical applications. There is potential for further research in this area, including expanding the waste classification dataset to cover more categories of waste and increasing the number of images to improve the accuracy of the model. Robotics and automation for handling mixed industrial waste is an emerging research field, but one that is expected to grow rapidly in the coming years as more researchers seek to create robots that can actively help toward a sustainable society in the future.

Furthermore, these vehicles have the potential to contribute to a cleaner environment by reducing emissions associated with traditional waste collection methods. In the long run, autonomous vehicles for garbage collection and sorting have the potential to revolutionize the waste management industry, making it more efficient, environmentally friendly, and costeffective.

Upon reviewing various papers, it was observed that different algorithms yielded varying accuracies in the context of automatic waste sorting by a robot arm on a conveyor belt. Table III below details the advantages and obstacles associated with waste sorting systems.

Author	Method	Merits	Challenges
Huang et.al., (2020)	Hybrid deep learning model (DenseNet 169, VGG19, and NASNetLarge)	94% overall classification accuracy	Accuracy for glass, paper, and textile wastes to be improved.
Ishika et.al, (2020)	CNN	83% average classification accuracy	Classification accuracy to be improved.
Wei Chen (2020)	ResNet-18	92% classification accuracy	High training time required.
Zhuang et.al., (2020)	ResNet-34	99% classification accuracy	High training time is required to train the system due to a large number of layers.
Nawako wski et.al., (2020)	CNN and Faster regionbased CNN (RCNN)	97% classification accuracy	Able to classify waste alone.
Abhishek et.al., (2021)	EfficientNet B3	92.8% classification accuracy	Detailed classification needs to be incorporated.
Santhiya et.al., (2021)	Deep convolutional neural network (DCNN) with stochastic gradient descent	Better classification accuracy than ANN, SVM, KNN, Naive Bayes	Results limited to specific garbage classification.
Boguski et.al., (2021)	CNN for plastic waste classification	Minimum parameters are used for the classification	Attains minimum classification accuracy of 74%.
Alsabei et.al., (2021)	Pre-trained CNN (ResNet50, VGG16, InceptionV3, and Xception) with GAN	Xception and VGG16 perform better than other algorithms	Attains minimum classification accuracy of 80%.
Qiang et.al., (2021)	ResNet	5.87%	Detailed Classification needs to be incorporated.
Bowen et.al., (2021)	Improved MobileNetV3	92.62% classification accuracy.	-
Cong et.al., (2021)	Variants of CNN	MobileNet V3 attains a better classification performance of 94.6%	-
Zhang et.al., (2021)	DenseNet 169	82% classification accuracy.	-
Zhen Yuan and Jinfeng Liu (2022)	Hybrid deep learning model	98.5% classification accuracy	High training time is required to train the system.
Xie et.al., (2022)	VGG16, ResNet50, DenseNet121, MobileNet V2, Inception V3	MobileNet V2 performed better than other algorithms with 98.75% classification accuracy	Multiple models are used and all are pretrained.
Sehrish et.al., (2022) Yi Zhao.et.al., (2022)	VGG16 Improved MobileNetV3 with LSTM	90% classification accuracy 81% classification accuracy	Classification accuracy to be improved. Classification accuracy to be improved.
Tran et.al., (2022)	ResNet-50	96% classification accuracy	Classifies inorganic or organic trash only.
Jiajia Li et.al., (2022)	Multimodal cascaded CNN		
Anthony et.al., (2022)	Pretrained CNN (ResNet-50, ResNet, MobileNetV2, enseNet, ShuffleNet, and A	ResNet performed better than other algorithms	Multiple models are used and all are pretrained.
Altikat et.al., (2022)	DCNN	83% classification accuracy	Classifies organic trash only.
Rahman et.al., (2022)	CNN	95.3% classification accuracy.	-
Sylwia et.al., (2022)	EfficientNet-B2	75% classification accuracy	Classification accuracy to be improved.
Tao et.al., (2022)	Machine learning algorithms	Artificial neural network performed better than other algorithms	Multiple models are used for Comparative analysis.

TABLE III
RESEARCH COMPARISON

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