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Deep Learning Architectures for Waste Detection: A Systematic Literature Review

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ABSTRACT

Increasing population growth contributes to the increasing amount of waste generated, creating problems in its management. One possible alternative is the usage of deep learning-based artificial intelligence technology, which can be applied for automated waste identification and classification. This research follows Systematic Literature Review (SLR) with the aim of evaluating the performance of various deep learning architectures in waste detection. Out of 547 articles identified, 20 were synthesized with the use of selective criteria. The synthesis of the evidence shows that architectures like YOLO, Faster R-CNN, and EfficientNet have been proven to be effective in the various datasets for waste detection. Furthermore, certain other models, such as ResNet-50B and DenseNet121, performed very well in image classification with accuracy values above 90%. In this research, several challenges were identified, including high computing power and computational magnitude. For future work, the optimization of models as well as the use of standard datasets such as TrashNet and TACO are recommended research directions that might help in developing an effective, efficient, and sustainable waste sorting system.

INTRODUCTION

One of the significant consequences of an increase in population in a region or city is an increase in waste volume. According to Pernando et al., waste is material that is removed or no longer used either by humans or natural processes because its main elements or functions have been taken [1]. According to the Ministry of Environment and Forestry of the Republic of Indonesia timestamped to 2023, the amount of waste generated amounted to 17,931,137.45 tons/day, with a mean of 49,126.40 tons per day. A large portion of the waste, 40.03% of it, comes from households, with markets following in second place at 19.58%, then commerce at 17.29%, regions at 8.25%, offices at 5.99%, public facilities at 5.92%, and other sources at 2.94% [2].

According to Law Number 18 of 2008, one of the solutions that can be taken is waste segregation in the form of grouping and separating waste according to the type, amount, and/or nature of the waste [3]. Frequently, waste that ought to be separated according to its type—such as hazardous, inorganic, and organic waste—is combined. As a result, the waste is not processed properly as it should be [4]. Furthermore, because waste is composed of so many different elements, waste disposers are occasionally perplexed by the sort of waste category they have [5]. Therefore, artificial intelligence comes as an alternative technology to assist in the process of sorting waste according to its type.

In waste management, the use of artificial intelligence has enormous potential. Deep learning, as a form of artificial intelligence, has an important role in the waste sorting process [6]. For instance, in order to determine the best classification model for waste classification, Muangnak et al. compared the deep learning architectures ResNet-50 and ResNet-152. This study used two types of datasets, namely the TrashNet dataset and a local dataset containing 5,326 images of four different waste categories (garbage, plastic, metal, and pets). The ResNet-152 and ResNet-50 experimental testing findings in this article showed improved accuracy of 95.72% and 94.15%, respectively [7].

In a different study, ResNet-101 was used to identify inorganic waste. 2,527 images belonging to six waste categories—cardboard, glass, metal, paper, plastic, and trash—were used in the study. From this research, an accuracy value of 92% was obtained for training data and 90% for testing data [8]. In addition, there is also research conducted by Pernando et al. on the application of the Single-Shot Detector (SSD) algorithm to detect and classify types of waste in real-time. The type of waste classified is divided into two classes, namely organic and inorganic waste. The results showed an average accuracy value of 93% [1].

The large number of studies using different deep learning architectures and algorithms for waste detection often leads to varying conclusions. In this regard, an in-depth review is warranted to determine which algorithm is most suited for the detection of waste. This systematic literature review research has been undertaken for the reason of eliminating the bias that may be brought about by previous studies. Such a study is expected to issue much better recommendations for practitioners and scholars in the selection of appropriate deep learning architecture and algorithms enhancing the performance of waste sorting and management.

METHOD

This research uses the Systematic Literature Review (SLR) method, which is an approach that aims to evaluate, determine, and interpret various related research findings to answer the questions that have been formulated. The SLR method allows researchers to conduct a structured review and identification of journals, with each stage following predetermined steps or protocols [9]. By combining empirical data to provide clear, reproducible answers to certain research questions, SLR seeks to compile all published works on the topic and assess the validity of this evidence [10]. This method involves several stages, including the formulation of the research question, literature search, inclusion and exclusion criteria, literature selection, data presentation, processing, and conclusion [11].

The concept is built based on the literature to answer three research questions: (1) What deep learning architectures are effective for waste detection; (2) Why deep learning technology is used for waste detection and what are its main advantages over conventional methods; (3) How deep learning architectures perform for waste detection. Based on the literature that has been taken, it can show several deep learning architectures that can be used for waste detection.

At the initial stage of the review, about 547 articles indexed in Scopus, DOAJ, and PubMed were collected. These articles were obtained using keywords such as “deep learning architecture for waste detection,” “advantages of deep learning,” and “deep learning architecture performance for waste detection.” The distribution of sources used in this study is shown in Figure 1.

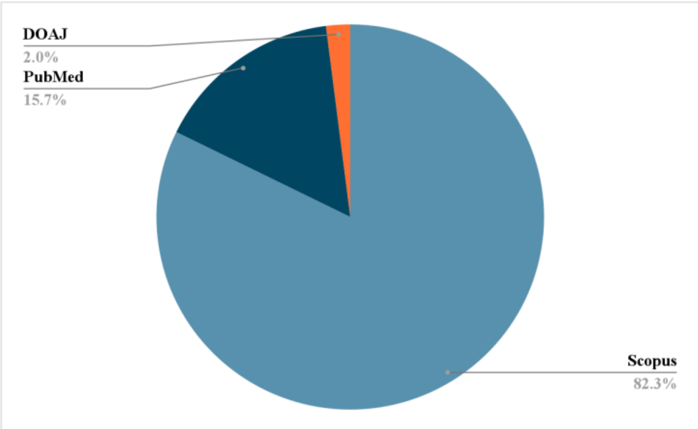

Figure 1. Source distribution of articles

The next step was the establishment of inclusion and exclusion criteria. The inclusion and exclusion criteria are displayed in Table 1.

Table 1. Inclusion and Exclusion Criteria.

Inclusion Criteria	**Exclusion Criteria**
Articles published on or after 2020	Articles published before 2020
Articles published in other official academic publication journals relevant to the research topic	Articles from conferences, books, or reviews in press
Articles with appropriate titles	Articles with inappropriate titles
Articles that have abstracts relevant to the research topic	Articles that have abstracts that are not relevant to the research topic
Articles available in full-text peer-reviewed journals	Articles without full text access (no full text)

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta Analysis) graphic in Figure 2 illustrates the steps involved in the literature selection process.

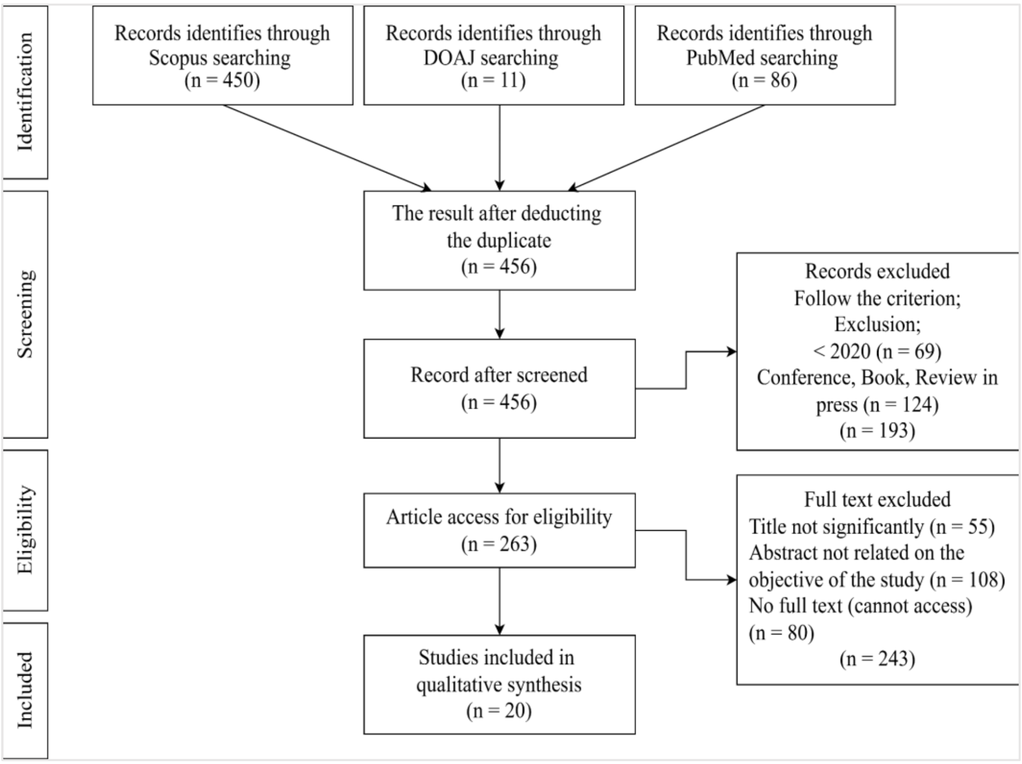

Figure 2. PRISMA flowchart

Figure 2 explains the article selection process, starting with initial identification using three main sources, namely Scopus, DOAJ, and PubMed, which resulted in a total of 547 articles. Of these, 450 articles came from Scopus, 11 articles came from DOAJ, and 86 articles came from PubMed. After duplicates were removed, 456 articles were retained. In the screening stage, 193 articles were eliminated based on exclusion criteria, such as articles published before 2020 or non-journal sources (conferences, books). Next, 263 articles were accessed to evaluate their eligibility. In this stage, 243 articles were eliminated for not meeting the criteria, including inappropriate titles, abstracts that were not relevant to the research topic, and lack of access to the full text. In the end, 20 articles passed the selection and were included in the qualitative analysis.

RESULT AND DISCUSSION

Result

In this literature review, data is grouped according to information on research, journals, research subjects, and research findings. The resulting literature analysis is in Table 2.

Table 2. Research Results on Deep Learning Architecture for Waste Detection

Research	Subject	Research Result
[12]	Various AI models and techniques	The results show that in object detection using deep learning methods, aspects that need attention are computational efficiency and the ability to handle objects of different sizes. To overcome these obstacles, various object detection architectures have been developed, such as R-FCN and Mask R-CNN. In addition, models with single-pass architectures such as YOLO, SSD, DSSD, and RetinaNet have also been introduced to support real-time detection. The use of these architectures greatly affects the accuracy and speed of object detection, especially in applications that require fast and efficient data processing.
[13]	7 types of waste (cans, cardboard, plastic bottles, foam, glass, paper, and plastic)	The findings have demonstrated the effectiveness of item recognition and tracking methods based on deep learning architecture in identifying floating trash in rivers, especially You Only Look Once (YOLOv5) and Simple Online and Realtime Tracking with a Deep Association Metric (DeepSORT). The improved YOLOv5 model achieved high classification accuracy, with a mean average precision of 88% or higher.
[14]	10 classes of waste (paper, paper packaging, paper cups, cans, bottles, PET, plastic, vinyl, lids, labels)	The results show that ARTD-Net1 with ResNext-101 backbone outperforms the other two models, YOLOX-X with Modified CSPDarknet v5 backbone and YOLOv6 with CSPStackRep backbone, according to the results. The F1 score and mAP of ARTD-Net1 with ResNext-101 are greater than those of YOLOX-X, at 0.275 and 0.004, respectively. With a mAP of 0.007 and an F1 score of 0.231, ARTD-Net1 also demonstrated dominance over YOLOv6.
[15]	3 types of hospital waste, MSG (Mask, Bio-hazard Symbol, Gloves)	The results reflect that object detection models, which either use anchor-based or anchor-free mechanisms, work quite differently. Among the anchor-based models, YOLOv3-spp, YOLOv4, and YOLOv5 obtained the highest mAP with 85.27%, while the anchor-free model, represented by YOLOX-l, with the highest mAP at 92.49%, performed better.
[16]	2 types of waste (organic and recyclable waste)	The results depict the performance comparison between the Improved DCNN model and other popular models-VGG16, VGG19, MobileNetV2, DenseNet121, and EfficientNetB0-after the transfer learning technique was applied. Through experimental results, the Improved DCNN model proposed has successfully achieved an image classification accuracy of 93.28%, which is very much higher compared to those by other models.
[17]	3 types of waste (metal, paper, and plastic)	Table 9 shows that Faster R-CNN ResNet-101 takes longer computation time compared to ResNet-50; however, it yields smaller total loss and higher F1 score, which is 0.1898 versus 0.1909 and 77% versus 63%, respectively. On the other hand, ResNet-50 is faster during training and testing but has lower training accuracy and quality. This may indicate a trade-off between time efficiency and model performance.
[18]	Municipal Solid Waste (MSW) (plastic, glass, metal, paper, and more)	The results proved the transfer learning technique enhanced the EfficientNet-B0 base model with better classification accuracy of the solid waste images. Additionally, by improvising further, the EfficientNet-B0 model attained a high value of classification accuracy as high as 85%, which had been limited to a maximum of 80% in previous studies. This may definitely make the EfficientNet-B0 model competitive even for the EfficientNet-B3 model within the same domain. However, this is an increase in accuracy for a certain set of images that fit into the category of waste. That would mean that transfer learning does help improve the model performance on specific datasets.
[19]	Images of garbage from	The results depict the performance of six object detection models, namely EfficientDet D1, Faster R-CNN ResNet101, SSD ResNet-50, CenterNet

Research	Subject	Research Result
	different scenes and directions, including street waste, household waste, and medical waste.	ResNet101, and YOLOv5M, on the Garbage Dataset. After training for 500 epochs, testing was done on 25 new images. Among these, YOLOv5M had the best performance in detecting the most trash-even trash around the trash can-followed by Faster R-CNN ResNet101 and EfficientDet-D1. The SSD ResNet-50 performed the worst since it didn't detect most of the waste. Furthermore, with mAP using a 0.5 IoU threshold, it is confirmed that YOLOv5M detects more accurately.
[20]	6 types of waste (cardboard, glass, metal, paper, plastic, kitchen waste)	In this work, SqueezeNet was chosen as the classification network training model due to its shorter prediction time with good accuracy compared to ResNet and InceptionV3. The SqueezeNet model was pre-trained on the ImageNet-1000 dataset, and transfer learning was applied, enhanced by image augmentation techniques and the use of Adam optimizer. After training, the prediction accuracy of the model reached 87.7%. Besides, the prediction time on a unified industrial machine is less than 2 seconds, meeting practical application needs.
[21]	4 types of waste (recyclable waste, hazardous waste, kitchen waste, and other waste)	This study uses the VGG16 Convolutional Neural Network (CNN) model to identify and classify domestic garbage, in an effort to apply deep learning in the field of environmental protection. The developed system classifies domestic garbage into four categories: recyclable garbage, hazardous garbage, kitchen waste, and other garbage. The test results show that the correct classification rate reaches 75.6%, which meets the needs of daily use.
[22]	TU Delft-Interaction between Particles and Biomass (TUD-IPB)	The results show that the Cascade Mask R-CNN model with ResNet50 backbone achieves promising detection accuracy, with mAP50box of 90.6% and mAP50mask on the test set. Furthermore, this method was compared with the conventional processing method ImageJ. The results showed that the deep learning (DL) method outperformed ImageJ in both detection accuracy and processing cost. The DL method provides an improvement of 13.8% in micro-average precision and 21.7% in micro-average recall over the ImageJ method.
[23]	7 categories of waste (metal, plastic, glass, paper, cardboard, general waste, and e-waste)	In this study, waste was categorized as metal, plastic, glass, paper, cardboard, general waste, and electronic waste using CNN. Its transfer learning algorithms put to test are Xception, DenseNet121, ResNet-50, MobileNetV2, and EfficientNetB7. Following the results, DenseNet121 achieved the highest result of 93.3%, while MobileNetV2 came second with an accuracy of 93%; ResNet-50, Xception, and EfficientNetB7 reached 92%, 92.5%, and 87%, respectively.
[24]	TrashNet Dataset - 4 types of waste (glass, paper, cardboard, plastic, and metal)	The results prove that the proposed model with the combination of the Buffalo Optimizer and Squeeze and Excitation Network improves the accuracy in waste classification. It performed much better compared to other CNN models by attaining a very high precision and recall of the model. The model was able to obtain a precision of 0.961 and recall of 0.962, with a mAP@0.5 of 0.968, proving superior performance against other models such as CNN, RNN, and LSTM.
[25]	5 types of waste (cardboard, glass, paper, plastic, and metal)	This study proposes a Lightweight Feature Fusion Single Shot Multibox Detector (L-SSD) model for waste detection that is developed based on the Single Shot Multibox Detector (SSD) network structure to replace VGG16 with ResNet-101. The results show that with these improvements and the use of an optimized network framework, the L-SSD algorithm achieves the best performance of 83.48%.
[26]	6 types of waste (glass, paper, cardboard, plastic, metal, and everyday waste)	Experiments show that SSD and Faster R-CNN significantly outperform other object detectors on the TrashNet dataset and other datasets of trash with the following precision: 97.63% and 95.76%, respectively. The best performance of MobileNetV2 SSD, pre-trained on OID, was managed to be achieved due to the optimization of the learning rate and fine-tuning.

Research	Subject	Research Result
		Simultaneously, Faster R-CNN showed better detection results in the case of small objects but lost to SSD in speed.
[27]	7 types of waste (organic waste, cardboard, paper, metal, glass, plastic, and other waste)	The InceptionNet model shows the best performance with 98.15% accuracy and 0.10 loss on the training dataset, and 96.23% and 0.13 on the validation dataset. The proposed system works optimally when high-resolution images of objects are faced with a white background. The accuracy of this model ranges from 96.23% to 98.15%, which is even better than the previous model.
[28]	Various DCNN deep learning architectures	Analysis of deep learning-based object detection algorithms shows significant progress in accuracy and speed, which is suitable for real-time applications. However, challenges still exist, such as the compromise between accuracy and computational speed, the difficulty of detecting small dense objects, as well as the robustness of the algorithm under various environmental conditions.
[29]	Mnist dataset and Corel1000 dataset	Experimental results show that traditional machine learning is more effective on datasets with small samples, while deep learning frameworks have higher recognition accuracy on datasets with large samples.
[30]	TrashNet dataset (plastic, paper, metal, and leaf waste)	This paper proposes the improved ResNet-50 for the garbage classification task, whose improvements have been made for feature filtering, down-sampling, and feature fusion. On the TrashNet dataset, the original ResNet-50 achieved an accuracy of 84.46%. When an attention module and the modified down-sampling method are added to ResNet-50A, it achieves an accuracy of 88.4% while reducing loss by nearly half. Finally, the ResNet-50-B model is augmented with multiscale feature fusion, achieving an accuracy of 92.08% with more considerable loss reduction.
[31]	Various methods used to detect image forgery, ranging from traditional methods to deep learning-based approaches.	Deep learning technology has performed very well in image forgery detection, improving the accuracy and robustness of detection remarkably. However, specific performance for these methods degrades with factors such as image quality, manipulation done, and post-processing methodology among others. Full testing requires standardized datasets and challenging benchmarks. Besides, on the practical side, large computational resources are required when using deep learning methods.

In Table 2, it can be explained that the results of research on deep learning architectures for waste detection, based on the journals used as sources, include several architectures such as Faster R-CNN, Mask R-CNN, YOLO, DeepSORT, ResNet, VGG, and MobileNet. These deep learning architectures show good performance based on evaluation metrics, such as accuracy, mean average precision (mAP), F1 score, IoU, precision, and recall.

It has several advantages compared to other deep learning architectures for object detection, including high accuracy, real-time detection speed, flexibility in handling complex objects, and adaptability to large-scale datasets. This makes it superior to traditional machine learning methods for modern object detection applications.

Discussion

This systematic literature review aims to identify effective deep learning architectures and evaluate their performance in waste detection. Based on the analysis of 20 relevant articles, three main themes have been obtained, namely deep learning architectures for waste detection, the performance of deep learning architectures for waste detection, and the advantages of deep learning architectures.

Deep Learning Architecture for Waste Detection

According to earlier research, different deep learning architectures have been applied to waste detection with varying effectiveness. A summary of the main findings related to deep learning architectures in waste detection can be seen in Table 3.

Table 3. Deep Learning Architecture for Waste Detection

No.	Deep Learning Architecture	Article Percentage	References
1	ARTD-Net 1 ResNet-101	1 (2.9%)	[14]
2	Cascade Mask R-CNN ResNet-50	1 (2.9%)	[22]
3	CenterNet ResNet-101	1 (2.9%)	[19]
4	Deep Association Metric (DeepSORT)	1 (2.9%)	[13]
5	DenseNet121	2 (5.9%)	[23], [16]
6	EffcientDet D1	1 (2.9%)	[19]
7	EfficientNet-B0	2 (5.9%)	[16], [18]
8	EfficientNet-B3	1 (2.9%)	[18]
9	EfficientNet-B7	1 (2.9%)	[23]
10	Faster R-CNN	1 (2.9%)	[26]
11	Faster R-CNN ResNet-101	2 (5.9%)	[17], [19]
12	Faster R-CNN ResNet-50	1 (2.9%)	[17]
13	InceptionNet	1 (2.9%)	[27]
14	Lightweight Feature Fusion Single Shot Multibox Detector (L-SSD)	1 (2.9%)	[30]
15	MobileNetV2	2 (5.9%)	[23], [16]
16	ResNet-50	2 (5.9%)	[23], [18]
17	ResNet-50A	1 (2.9%)	[18]
18	ResNet-50B	1 (2.9%)	[18]
19	Single Shot Detector (SSD)	1 (2.9%)	[26]
20	Squeeze and Excitation Network (SEN)	1 (2.9%)	[24]
21	SqueezeNet	1 (2.9%)	[20]
22	SSD ResNet-50	1 (2.9%)	[19]
23	VGG-16	2 (5.9%)	[16], [21]
24	VGG-19	1 (2.9%)	[16]
25	Xception	1 (2.9%)	[23]
26	You Only Look Once (YOLO)	3 (8.8%)	[15], [13], [19]

Table 3 lists the various deep learning architectures that have been used for waste detection, with YOLO being the most popular (8.8%) due to its real-time detection capability with high accuracy ([15]; [13]). DenseNet121 and MobileNetV2 (5.9%) showed flexibility in various applications ([23]; [16]). As for efficiency, L-SSD recorded an mAP of 83.48% with the modification of standard SSD architecture ([30]). Various datasets, such as TrashNet and TACO demonstrate the flexibility of these architectures in various contexts of waste detection.

Performance of Deep Learning Architecture for Waste Detection

The synthesized results show that most of the deep learning architectures used for waste detection exhibit superior performance in various evaluation metrics. A summary of the performance of deep learning architectures for waste detection is presented in Table 4.

Table 4. Performance of Deep Learning Architecture for Waste Detection

Reference	**Datasets**	**Methods**	**Evaluation**
[13]	7 types of waste (cans, cardboard, plastic bottles, foam, glass, paper, and plastic)	You Only Look Once (YOLOv5) and Simple Online and Realtime Tracking with a Deep Association Metric (DeepSORT)	mAP: 88.0%
[14]	10 classes of waste (paper, paper packaging, paper	ARTD-Net 1 with ResNext-101	mAP: 0.007 F1: 0.231

Reference	Datasets	Methods	Evaluation
	cups, cans, bottles, PET, plastic, vinyl, lids, labels)		
[15]	3 types of hospital waste, MSG (Mask, Biohazard Symbol, Gloves)	Anchor-based model: YOLOv3-spp, YOLOv4, YOLOv5 Anchor-free based model: YOLO X-1	Anchor mAP: 85.27% Anchor-free mAP: 92,49%
[16]	2 types of waste (organic and recyclable waste)	Improved DCNN	acc: 93.28%
[17]	3 types of waste (metal, paper, and plastic)	Faster R-CNN ResNet-50 and Faster R-CNN ResNet-101	Faster R-CNN ResNet-50 loss: 0.1898 F1: 77% Faster R-CNN ResNet-50 loss: 0.1909 F1: 63%
[18]	Municipal Solid Waste (MSW) (plastic, glass, metal, paper, and more)	EfficientNet-B0 and EfficientNet-B3	EfficientNet-B0 acc: 85% EfficientNet-B3 acc: 80%
[19]	Images of garbage from different scenes and directions, including street waste, household waste, and medical waste.	EfficientDet-D1, SSD ResNet-50 FPN, Faster R-CNN ResNet-101, CenterNet ResNet-101 FPN, and YOLOv5M	EfficientDet-D1 mAP: 0.360 SSD ResNet-50 mAP: 0.511 Faster R-CNN ResNet-101 mAP: 0.586 CenterNet ResNet-101 FPN mAP: 0.595 YOLOv5M mAP: 0.613
[20]	6 types of waste (cardboard, glass, metal, paper, plastic, kitchen waste)	SqueezeNet	acc: 87.7%
[21]	4 types of waste (recyclable waste, hazardous waste, kitchen waste, and other waste)	VGG16	acc: 75.6%
[22]	TU Delft-Interaction between Particles and Biomass (TUD-IPB)	Cascade Mask R-CNN with ResNet-50	mAP: 90.6%
[23]	7 categories of waste (metal, plastic, glass, paper, cardboard, general waste, and e-waste)	Xception, DenseNet121, ResNet-50, MobileNetV2, and EfficientNetB7	Xception acc: 92.5% DenseNet121 acc: 93.3% ResNet-50 acc: 92% MobileNetV2 acc: 93%

Reference	Datasets	Methods	Evaluation
			EfficientNetB7 acc: 87%
[24]	TrashNet Dataset - 4 types of waste (glass, paper, cardboard, plastic, and metal)	Squeeze and Excitation Network (SEN)	prec: 0.961 rec: 0.962 mAP: 0.968
[25]	5 types of waste (cardboard, glass, paper, plastic, and metal)	Lightweight Feature Fusion Single Shot Multibox Detector (L-SSD)	mAP: 83.48%
[26]	6 types of waste (glass, paper, cardboard, plastic, metal, and everyday waste)	Single Shot Detector (SSD) and Faster R-CNN	SSD prec: 97.63% Faster R-CNN prec: 95.76%
[27]	7 types of waste (organic waste, cardboard, paper, metal, glass, plastic, and other waste)	InceptionNet	acc: 98.15% loss: 0.10
[30]	TrashNet dataset (plastic, paper, metal, and leaf waste)	ResNet-50, ResNet-50A, and ResNet-50B	ResNet-50 acc: 84.46% ResNet-50A acc: 88.4% ResNet-50B acc: 92.08%

Based on Table 4, various deep learning architectures show varying performance in waste detection according to the purpose and complexity of the dataset used. YOLOv5 and DeepSORT, as reported by [13], are effective for real-time waste detection with a mAP of 88%. Anchor-free models such as YOLOX-l excel in object detection over anchor-based models, recording the highest mAP of 92.49% [15]. For advanced classification, the Squeeze and Excitation Network (SEN) applied to the TrashNet dataset achieved a precision of 0.961, recall of 0.962, and mAP of 0.968, making it one of the best models for detecting and classifying trash [24]. These findings indicate that proper architecture selection can improve the effectiveness of waste detection in both real-time and non-real-time applications.

The Advantages of Deep Learning Architectures

Based on the data in Table 2, the deep learning architecture shows a number of significant advantages over traditional methods for waste detection:

1. High Accuracy
   Deep learning models like ResNet-50, DenseNet121, and YOLOv5 achieve up to 93.3% accuracy and 92.49% mAP, outperforming traditional methods on large and complex datasets.
2. Efficient Large Dataset Processing
   Models such as EfficientNet-B0 and Faster R-CNN handle large datasets like MSW and TrashNet with better accuracy than conventional approaches.
3. Transfer Learning
   EfficientNet-B7 and MobileNetV2 leverage transfer learning to adapt effectively to new datasets, a challenge for traditional methods.
4. Real-Time Detection
   YOLO and SSD enable high-speed, accurate object detection, ideal for real-time applications.
5. Handling Complex Variations
   Cascade Mask R-CNN and CenterNet excel in detecting objects with diverse sizes, shapes, and orientations, surpassing traditional techniques.

CONCLUSION

Based on the results of this systematic literature review, several deep learning architectures show great potential for optimized waste detection. Models such as YOLO, Faster R-CNN, and EfficientNet are proven to have high accuracy and efficiency in various applications, while ResNet-50B and DenseNet121 offer superior classification performance through transfer learning techniques. For applications that require real-time and lightweight detection, SSD and MobileNetV2 are recommended due to their efficiency and adaptability for embedded or mobile device-based systems.

For future research, a hybrid model that combines the advantages of YOLO for fast detection and ResNet-50B or DenseNet121 for high accuracy is recommended. Datasets such as TrashNet, TACO, or new datasets covering different types of waste and environments are also recommended to improve the generalizability of the model. This approach is expected to result in a reliable, efficient, and sustainable waste detection system.

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