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A Sustainable Approach to Waste Detection and Classification using YOLO: A Review

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***Abstract*— The increasing volume of discarded materials worldwide requires advanced waste management strategies to address environmental pollution and promote sustainability. The long-term environmental impacts of waste highlight the importance of proper identification, sorting, and utilization of different waste categories. This review paper synthesises recent advancements in approaches for waste segregation, focusing on computer vision (CV) and deep learning algorithms, particularly various variants of the YOLO (You Only Look Once) model. There are different models with efficacy in identifying waste and its categories. But, still challenges remain with these models. This paper presents a methodology for managing waste sustainably by using classification and feedback systems, which helps in improving the accuracy of the model. Along with studying different papers, this work shows the methods, datasets and performance in each paper. The analysis focuses on these technologies mainly in terms of accuracy, processing time so as to promote sustainable waste management in real life.**

Keywords*— Deep Learning models, computer vision (CV), waste detection and classification, YOLO, transfer learning, waste management, object segmentation.

I. INTRODUCTION

Poor waste management has become a bigger environmental problem leading to soil loss, dirty water, and more greenhouse gases. When trash isn't handled well in cities, it can cause real trouble. It can kill animals, pollute ecosystems, and put people's health at risk. When people don't sort their waste , it makes things worse. This means less recycling gets done, we need more landfills, and the environment suffers more. These days, we need a way to spot and group different types of waste so we can get rid of it the right way.

In waste detection and classification, Convolutional Neural Networks (CNNs) are trained on large data sets of labeled waste images in order to identify and classify various types of waste such as plastic, metal, glass, organic, non-recyclable materials. Using YOLO's capabilities, the system ensures accurate waste identification, allowing for more efficient sorting and disposal. This not only reduces the burden on landfills, but also encourages recycling and recovery, contributing to the circular economy. The integration of such solutions into existing waste management systems ensures flexibility, reduces manual labor, and supports global sustainability goals to reduce environmental pollution.

This paper gives an overall and thorough review of the methods currently performing well for smart waste management. We have also examined the benefits and shortcomings of different techniques such as CNNs, Mask R-CNN, EfficientNet, ResNet and other object detection algorithms like YOLO. A complete study of waste classification techniques is given along with how our proposed methodology supports accurate and sustainable waste management practices.

II. RELATED WORKS

In this section, an overview of the techniques proposed in the collected studies based on waste identification and classification is given. It covers the gradual development from initial deep learning models, like CNNs and R-CNN variations, to more complicated algorithms like YOLO. By focusing on the advantages and findings of these models, we will show how each technique has contributed to a better waste management system. We will also concentrate on different versions of YOLO models and traditional deep learning methods to accurately and swiftly detect objects in cluttered or complex situations.

The study [11] introduces two new datasets: Detect-Waste for trash identification and Classify-Waste for waste classification by combining more than 10 datasets, with various classes like bio, glass, metal and plastic. This was done because there were no standard datasets till then. They have used EfficientDet-D2 for trash localization and EfficientNet-B2 for classification and used semi-supervised learning for labeling the unlabeled data.

ScrapNet introduces a new method for waste classification using deep learning to tackle issues in waste management. The authors created a dataset called ScrapNet, which includes 8,135 images, and used the EfficientNet structure to categorize waste into seven groups: plastic, metal, glass, paper, cardboard, compost, and general trash. By using transfer learning with pre-trained ImageNet weights and testing different optimizers such as RMSProp, Adam, and SGD, the model reached an impressive 92.87% accuracy on the ScrapNet dataset and 98.4% on TrashNet. They also added a classification for plastics to distinguish them between recyclable and non-recyclable types.[12]

The paper [13] presents a deep learning approach for coastal waste detection using the Faster R-CNN framework to improve automatic waste sorting in coastal areas. The model incorporates feature fusion in addition to high-resolution, high-dimensional feature maps together to enhance small feature detection. RoI Align is used to eliminate positioning errors caused by RoI pooling, and k-means clustering is used to generate custom anchor boxes to fit the dataset. Data enhancement techniques are used to improve the training data and reduce overfitting. This model performed better than existing methods such as SSD, achieving 83.0% accuracy (mAP) with good accuracy in detecting small objects.

The following paper [14] focuses on waste material classification using deep learning models to improve solid waste management. It compares the performance of four models: ResNet50, GoogleNet, InceptionV3, and Xception. These models classify waste into four categories: cardboard, glass, metal, and miscellaneous trash. Data augmentation, a technique to artificially increase dataset size by modifying images (like flipping or rotating), was used to enhance accuracy. CNNs were used to get important features from the images, improving the classification process. The metrics used for evaluation were accuracy, precision, recall and F1-score. Among the models, the model with highest accuracy of 98% was InceptionV3, followed by ResNet with 95% accuracy and GoogleNet with 90% accuracy. Models like ResNet 50 and Xception had shown difficulty in performing glass classification.

The paper [15] proposed a new architecture, Multimodel Cascaded Convolutional Neural Network (MCCNN) for waste classification. It combines three deep learning models: DSSD, YOLOv4, and Faster-RCNN. These models are known for better performance in detecting the waste. This paper also utilised a custom dataset, LSWID, which includes 30,000 images across 52 waste categories. Techniques of data augmentation like random brightness changes, mirroring, stretching were used on the data. This method integrated detection and classification models in a cascade to improve accuracy. In this system, each image is processed under 500ms time. As a result, the proposed model obtained over 60% mAP and 10% improvement in detection precision. Also, they designed a Smart Trash Can system to classify the waste in real-time to enhance the efficiency of recyclability.

The challenges of the existing YOLOv3 model are addressed by the Skip-YOLO [16] model. In the paper [16], they enhanced the prediction of different types of wastes by performing receptive field expansion and combining high-dimensional feature maps. This has resulted in improvement in waste prediction in complex real-time circumstances. The model uses large convolution kernels for analyzing feature maps and dense convolutional blocks for deep feature extraction, followed by YOLO layers for end-to-end detection. Compared to YOLOv3, Skip-YOLO shows a 22.5% increase in detection accuracy and an 18.6% rise in recall rate, proving its effectiveness in detecting household waste in diverse settings.

The next paper [17] focuses on waste object detection and classification using YOLOv4 and YOLOv4-tiny, two deep learning models built on the Darknet-53 architecture. It highlights the importance of improving waste sorting methods, starting from households to final disposal sites. The dataset used for training was pre-processed using Mosaic data augmentation, which combines multiple images to improve model generalization, and labeled with a tool called LabelImg. Both YOLOv4 and YOLOv4-tiny were trained using transfer learning, where pre-trained weights from the COCO dataset. The models were evaluated using metrics such as mAP, precision, recall, F1-score, and Average IoU (Intersection over Union, which checks how well the predicted bounding boxes match the actual ones). YOLOv4 showed a mean average precision of 89.59%, which makes it the better-performing model, whereas YOLOv4-tiny, which was faster than the former, had a slightly lower precision of 81.84%.

In the study [18], the authors concentrated on detection of garbage items in outdoor environments, especially in underdeveloped areas like Bangladesh where physical trash sorting is not very effective. They have collected a dataset consisting of 4418 pictures, with 10 types of garbage. Then they tested the variants of YOLOv5 (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x), to find the better model among them for detecting different types of waste. They have also used transfer learning with weights from the COCO dataset to improve efficiency. The results showed that YOLOv5x has performed the best, with a precision of 84.4% which means it is very effective among the other variants.

In paper [19], the authors focused on finding items in cluttered waste areas by utilizing different computer vision methods. These include using top object detection models - Faster RCNN, Cascade RCNN, Retinanet, YOLOv8 and Mask - RCNN respectively. The images used are from cameras on garbage trucks. The models were trained from the beginning and also used pre-trained weights from COCO. YOLOv8, the newest version of the YOLO series, did the best, with a mean Average Precision (mAP) of 0.463. This was because it doesn't need anchors and works quickly. This study shows that modern deep learning models can be very effective for finding contaminants in difficult, cluttered waste situations.

Table. 1. Related Works Review

Ref. No.	**Key Technique**	**Dataset**	**Findings**
[11]	EfficientDet-D2, EfficientNet-B2	Detect-Waste and Classify-Waste	Semi-supervised learning, integrated over 10 datasets, waste identification (70%) and classification (75%).
[12]	EfficientNet with transfer learning	ScrapNet (8,135 images)	Classifies waste into 7 groups, subclassifies plastics, achieved 92.87% accuracy (ScrapNet) and 98.4% (TrashNet).
[13]	Faster R-CNN	Coastal Waste Dataset	Feature fusion, high-resolution maps, k-means clustering, RoI Align; achieved 83.0% mAP for detecting small objects.
[14]	ResNet50, GoogleNet, InceptionV3, Xception	Custom dataset	Waste classification into 4 categories; data augmentation, best model (InceptionV3) achieved 98% accuracy.
[15]	MCCNN (DSSD, YOLOv4, Faster-RCNN)	LSWID (30,000 images, 52 categories)	Cascade architecture, Smart Trash Can system, real-time processing (<500ms), 10% improvement in detection precision, mAP > 60% (Faster-RCNN).
[16]	Skip-YOLO	Custom dataset	Large receptive field, multiscale feature maps, dense convolutional blocks; improved detection accuracy (22.5%) and recall rate (18.6%) over YOLOv3.

[17]	YOLOv4, YOLOv4-tiny	Custom dataset with Mosaic augmentation	Improved waste sorting accuracy; mAP of 89.59% (YOLOv4) and 81.84% (YOLOv4-tiny), used transfer learning with COCO weights.
[18]	YOLOv5 variants (s, m, l, x)	4,418 images covering 10 trash categories	Effective for natural outdoor environments, mAP of 84.4% (YOLOv5x) with transfer learning using COCO weights.
[19]	Faster-RCNN, Cascade-RCNN, Retinanet, YOLOv8, Mask-RCNN	Garbage truck camera images	Focus on cluttered waste; YOLOv8 achieved highest mAP (0.463), anchor-free detection, and fast processing.

he reviewed studies show big improvements in identifying, sorting, and searching for waste items using deep learning methods. The authors built and studied special datasets like Detect-Waste, ScrapNet, and LSWID, and used top models like YOLOv8, EfficientNet, Mask-RCNN, and Faster-RCNN to solve important waste problems. Methods like transfer learning, augmentation, feature fusion, and custom anchor boxes for finding items have made the models better at spotting waste. Models like Skip-YOLO and YOLOv5x do well in tricky and natural places, and new ideas like MCCNN and Smart Trash Can could help with real-time waste sorting. All these efforts show that deep learning can make waste management systems work better, faster, and on a bigger scale, leading to more automatic and green ways to sort waste.

III. CHALLENGES IN EXISTING WORKS

Although the existing models have shown good results and computational efficiency, there are some limitations that persist. They are:

- Previous models struggled with accurately detecting small or irregularly shaped waste items, as well as handling multiple overlapping items in the same frame.
- Also, certain waste items (like plastic and glass bottles, tin cans and batteries) which look visually similar,but are differently disposed were misclassified.
- These works did not focus on segmentation of images which results in an output cluttered with bounding boxes.
- A feedback mechanism is essential for continuous improvement, allowing users to report errors in classification or detection, which can then be used to fine-tune the model over time.
- Limited availability of robust and diverse datasets.
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IV. METHODOLOGY

In this section, we outline the methodology employed for developing an effective waste detection and classification system. Building on insights gained from previous works and deep learning models, particularly those leveraging YOLO for object detection, this approach incorporates contemporary t models to address the complexities of identifying and classifying various waste types. To make the waste management tasks more efficient, this model proposes the combined usage of YOLOv7 for object detection, Mask R-CNN for pixel level segmentation and EfficientNet for class refinement. This methodology outlines the model selection, training, and feedback mechanisms that drive the system, leading to improved waste detection and classification performance. The architecture and workflow are detailed in the following sections.

A. Dataset

We are considering using TrashNet as the base dataset for our work, which comprises 7 categories—cardboard, paper, plastic, e-waste, glass, metal, and medical waste—each containing subclasses; additionally, we expanded our dataset by incorporating more subclasses.

The dataset consists of the following fields: Image id, class label, bounding box coordinates, class name, sub class name.

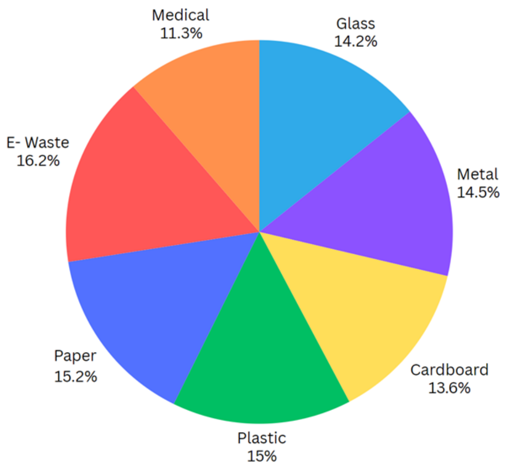

Fig. 1. Distribution of trash images in trashbox dataset

Table. 2. Trashbox dataset- Classwise statistics

Trash Classes	**Sub-classes**	**No. of images**
Cardboard	Assorted cardboard objects	2414
E-waste	Electrical chips	615
	Laptops & smartphones	774
	Small appliances	926
	Electric wires	568
Glass	Assorted glass objects	2528
Medical waste	Syringes	507
	Surgical gloves	496
	Surgical masks	500
	Medicines	507
Metal	Beverage cans	1000
	Construction scrap	539
	Spray cans	502
	Metal containers	505
	Miscellaneous metal	42
Plastic	Plastic bags	504
	Plastic bottles	571
	Plastic containers	508
	Plastic cups	507
	Cigarette butts	579
Paper	Tetra pak	794
	News paper	200
	Paper cups	639
	Other paper objects	1062

B. Architecture of Waste Detection and Classificication System

The architecture gives a full-cycle approach for waste detection, classification and disposal method recommendations. It incorporates the models YOLOv7 and Mask R-CNN along with a user feedback loop to increase the performance of the model eventually.

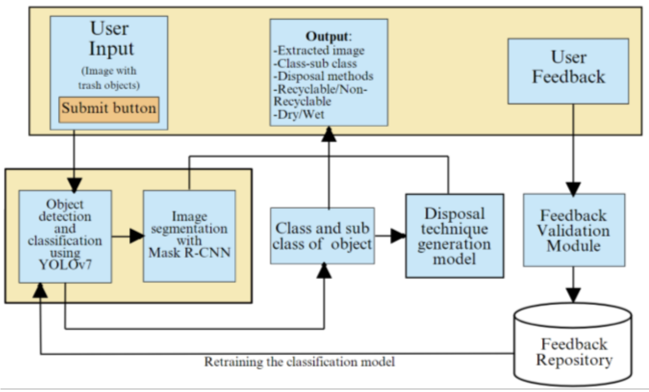

Fig. 2. Architecture. (Waste Detection and Classification system)

User input: Users upload images containing trash objects via a web interface, where they interact with a simple "Submit" button.

Item Detection and Classification Using YOLOv7: Once the image is submitted, the system applies YOLOv7 (You Only Look Once, Version 7) to identify and classify objects (trash) within the image based on predefined categories.

Image Segmentation Using Mask R-CNN: For more detailed and precise extraction, the system uses Mask R-

CNN and generates pixel-level masks for each detected object, providing precise segmentation of each trash item.

Class and Subclass of Objects: The system extracts the class and subclass of the detected and segmented objects. These categories can include cardboard, glass, paper, plastic, metal and e-waste and their subclasses refer to more specific waste types (eg: wires, devices and batteries are some subclasses in e-waste).

Disposal Technique Generation Model: Based on the class and subclass generated by the model, the generative model recommends methods to discard the waste items. For example, batteries must be disposed of after taping the ends to prevent fire and they must be dropped off in an authorized recycling centre.

User Feedback: After the prediction is displayed on the output screen, if the user feels that the prediction is wrong, they may provide feedback. The feedback is collected using a list of options from which the user can select the class and subclass which may seem correct to them.

Feedback Validation Module: After the feedback is given by the user, it cannot be blindly added to the repository because it may be faulty feedback. Therefore, this module is introduced for the sole purpose of checking if the given feedback is correct or not. It filters out the wrong feedback ensuring the valid data is used for retraining the model.

Feedback Repository: This is a data storage unit allocated for storing the valid feedback filtered out by the feedback validation module. From time to time, this data is used to retrain the model.

C. Workflow of Waste Detection and Classification model

The proposed workflow includes a system to improve waste detection, classification and disposal technique recommendation and achieve accurate predictions.

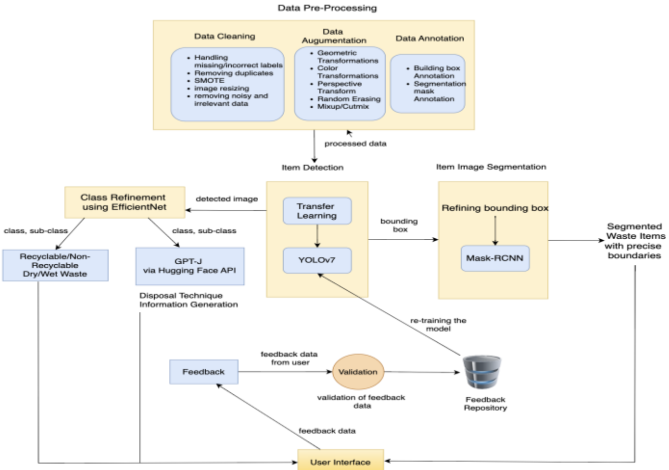

Fig. 3. Workflow. (Waste Detection and Classification model)

Data pre-processing: Initially, we handle missing or incorrect labels, remove duplicate entries, resize images to balance the dataset. We filter the noisy or irrelevant data to enhance the quality of input images. Next, we apply different transformation techniques to prevent overfitting and increase the variety of the data. And for object detection, as we need labelled data, we need to perform data annotation for bounding boxes and segmentation masks for mask annotations to prepare data for the model.

Item Detection with YOLOv7 and Transfer Learning: We will use transfer learning with the YOLOv7 model by utilising the relevant pre-trained weights of waste categories available in YOLOv7 to obtain efficient detection of waste items and generate bounding boxes.

Image Segmentation with Mask R-CNN: The bounding boxes from YOLOv7 are refined further using Mask R-CNN which enables precise segmentation. It provides accurate segments for detected waste items. This is useful to determine the items even if they are overlapped or clustered in the input image and avoids confusion.

Class Refinement Using EfficientNet: It is employed to further refine the detected object's class and subclass, ensuring accurate classification. The system determines if the waste is recyclable, non-recyclable, or wet/dry.

GPT-J Integration for Disposal Technique Information: Using GPT-J via the Hugging Face API, the disposal recommendation model generates personalised and context-aware instructions on how to dispose of the classified waste based on the class and subclass identified.

User Feedback: The user provides feedback on the model's classification and disposal recommendation via the user interface. This feedback is collected for validation before being used to further retrain the model. This feedback can be positive (if the prediction is correct) or negative (if the prediction is incorrect).

Feedback Validation: The feedback undergoes a validation process, where incorrect feedback is filtered out, ensuring only accurate feedback is sent to the repository and later used for model retraining.

Feedback Repository: The valid feedback data is stored in a temporary in-memory data store called redis cache allowing frequent and fast retraining.

Retraining of the Model: Validated feedback is stored in the feedback repository and used to iteratively improve the model through retraining, ensuring the system gets better over time.

V. CONCLUSION

In this study, we examined different models and techniques for waste detection and classification. As our goal is to automate the sorting mechanism and recommend disposal techniques, we reviewed several approaches regarding this and decided to select the YOLOv7 and Mask R-CNN models for our work as they provide balance between faster and accurate object detection and segmentation. The models YOLOv7, which is fast and detects objects in real time and Mask R-CNN, which offers pixel level accuracy, helps in accurately classifying the waste and building an efficient automated waste management system. We also considered the implementation of reinforcement learning technique for feedback feature, where the model learns from valid user input which helps in improving classification accuracy and enhancing its performance in real-word conditions.

REFERENCES

[1] Zhang, Qiang, Qifan Yang, Xujuan Zhang, Wei Wei, Qiang Bao, Jinqi Su, and Xueyan Liu. "A multi-label waste detection model based on transfer learning." Resources, Conservation and Recycling 181 (2022): 106235.

[2] Yang, Weizhi, Yi Xie, and Peng Gao. "Improved Method for Oriented Waste Detection." Axioms 12, no. 1 (2022): 18.

[3] Yaohui, Hou. (2022). Detection of Domestic Waste Based on YOLO. Frontiers in Computing and Intelligent Systems, 2(1), 126-128. doi: 10.54097/fcis.v2i1.3182

[4] Liu, Xuetao. "Real-Time Classification and Detection of Garbage Based on Improved Yolov5 and Embedded System." In 2023 12th International Conference of Information and Communication Technology (ICTech), pp. 333-341. IEEE, 2023.

[5] Desta, Meron, Tagel Aboneh, and Bisrat Derebssa. "Deep learning-based object detection for smart solid waste management system." Annals of Environmental Science and Toxicology 7, no. 1 (2023): 052-060.

[6] He, Yanhong, and Junfeng Li. "TSRes-YOLO: An accurate and fast cascaded detector for waste collection and transportation supervision." Engineering Applications of Artificial Intelligence 126 (2023): 106997.

[7] Fan, Jinhao, Lizhi Cui, and Shumin Fei. "Waste detection system based on data augmentation and YOLO_EC." Sensors 23, no. 7 (2023): 3646.

[8] Ma, Wanqi, Hong Chen, Wenkang Zhang, Han Huang, Jian Wu, Xu Peng, and Qingqing Sun. "DSYOLOtrash: An attention mechanism-integrated and object tracking algorithm for solid waste detection." Waste Management 178 (2024): 46-56.

[9] Ren, Yuanming, Yizhe Li, and Xinya Gao. "An MRS-YOLO Model for High-Precision Waste Detection and Classification." Sensors 24, no. 13 (2024): 4339.

[10] Li, Pan, Jiayin Xu, and Shenbo Liu. "Solid Waste Detection Using Enhanced YOLOv8 Lightweight Convolutional Neural Networks." Mathematics 12, no. 14 (2024): 2185.

[11] Majchrowska, Sylwia, et al. "Deep learning-based waste detection in natural and urban environments." Waste Management 138 (2022): 274-284.

[12] Masand, Abhishek, Suryansh Chauhan, Mahesh Jangid, Rajesh Kumar, and Satyabrata Roy. "Scrapnet: An efficient approach to trash classification." IEEE access 9 (2021): 130947-130958.

[13] Ren, Chengjuan, Hyunjun Jung, Sukhoon Lee, and Dongwon Jeong. "Coastal waste detection based on deep convolutional neural networks." Sensors 21, no. 21 (2021): 7269.

[14] Al-Mashhadani, Israa Badr. "Waste material classification using performance evaluation of deep learning models." Journal of Intelligent Systems 32, no. 1 (2023): 20230064.

[15] Li, Jiajia, et al. "Automatic detection and classification system of domestic waste via multimodel cascaded convolutional neural network." IEEE transactions on industrial informatics 18.1 (2021): 163-173.

[16] Lun, Zhao, Yunlong Pan, Sen Wang, Zeshan Abbas, Md Shafiqul Islam, and Sufeng Yin. "Skip-YOLO: Domestic garbage detection using deep learning method in complex multi-scenes." International Journal of Computational Intelligence Systems 16, no. 1 (2023): 139.

[17] Andhy Panca Saputra, Kusrini. "Waste Object Detection and Classification using Deep Learning Algorithm: YOLOv4 and YOLOv4-tiny." Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12.14 (2021): 1666-1677

[18] Das, Dhrubajyoti, Kaushik Deb, Taufique Sayeed, Pranab Kumar Dhar, and Tetsuya Shimamura. "Outdoor Trash Detection in Natural Environment Using a Deep Learning Model." IEEE Access (2023).

[19] Mewada, Dishant, Cathaoir Agnew, Eoin M. Grua, Ciarán Eising, Patrick Denny, Mark Heffernan, Ken Tierney, Pepijn Van De Ven, and Anthony Scanlan. "Contamination Detection from Highly Cluttered Waste Scenes using Computer Vision." IEEE Access (2024).

[20] Shi, Cuiping, Cong Tan, Tao Wang, and Liguo Wang. "A waste classification method based on a multilayer hybrid convolution neural network." Applied Sciences 11, no. 18 (2021): 8572.

[21] Rahman, Md Wahidur, Rahabul Islam, Arafat Hasan, Nasima Islam Bithi, Md Mahmodul Hasan, and Mohammad Motiur Rahman. "Intelligent waste management system using deep learning with IoT." Journal of King Saud University-Computer and Information Sciences 34, no. 5 (2022): 2072-2087.

[22] Abdu, Haruna, and Mohd Halim Mohd Noor. "A survey on waste detection and classification using deep learning." IEEE Access 10 (2022): 128151-128165.

[23] Wang, Jianfei. "Application research of image classification algorithm based on deep learning in household garbage sorting." Heliyon 10, no. 9 (2024).

[24] Kumsetty, Nikhil Venkat, Amith Bhat Nekkare, and Sowmya Kamath. "Trashbox: trash detection and classification using quantum transfer learning." In 2022 31st Conference of Open Innovations Association (FRUCT), pp. 125-130. IEEE, 2022.

[25] Funch, Oliver Istad, Robert Marhaug, Sampsa Kohtala, and Martin Steinert. "Detecting glass and metal in consumer trash bags during waste collection using convolutional neural networks." Waste management 119 (2021): 30-38.

[26] He, Yanhong, Junfeng Li, Shuhang Chen, Yining Xu, and Jia Liang. "Waste collection and transportation supervision based on improved YOLOv3 model." IEEE Access 10 (2022): 81836-81845.

[27] Sallang, Nicholas Chieng Anak, Mohammad Tariqul Islam, Mohammad Shahidul Islam, and Haslina Arshad. "A CNN-based smart waste management system using TensorFlow lite and LoRa-GPS shield in Internet of Things environment." IEEE Access 9 (2021): 153560-153574.

[28] Yang, Jianfei, Zhaoyang Zeng, Kai Wang, Han Zou, and Lihua Xie. "GarbageNet: a unified learning framework for robust garbage classification." IEEE Transactions on Artificial Intelligence 2, no. 4 (2021): 372-380.