www.nature.com/scientificdata

scientific data

Check for updates

OPEN

DATA DESCRIPTOR

A benchmark dataset for class-wise segmentation of construction and demolition waste in cluttered environments

Diani Sirimewan[1] ✉, Sanuwani Dayarathna[2], Sudharshan Raman[3], Yu Bai[1] & Mehrdad Arashpour[1]

Efficient management of construction and demolition waste (CDW) is essential for enhancing resource recovery. The lack of publicly available, high-quality datasets for waste recognition limits the development and adoption of automated waste handling solutions. To facilitate data sharing and reuse, this study introduces 'CDW-Seg', a benchmark dataset for class-wise segmentation of CDW. The dataset comprises high-resolution images captured at authentic construction sites, featuring skip bins filled with a diverse mixture of CDW materials in-the-wild. It includes 5,413 manually annotated objects across ten categories: concrete, fill dirt, timber, hard plastic, soft plastic, steel, fabric, cardboard, plasterboard, and the skip bin, representing a total of 2,492,021,189 pixels. Each object was meticulously annotated through semantic segmentation, providing reliable ground-truth labels. To demonstrate the applicability of the dataset, an adapter-based fine-tuning approach was implemented using a hierarchical Vision Transformer, ensuring computational efficiency suitable for deployment in automated waste handling scenarios. The CDW-Seg has been made publicly accessible to promote data sharing, facilitate further research, and support the development of automated solutions for resource recovery.

Background & Summary

The construction industry is crucial in driving global economic growth, significantly contributing to gross domestic product[1]. Rapid population growth, urbanisation, and industrialisation have intensified the demand for housing, infrastructure, and urban environments[2]. This surge in demand leads to substantial amounts of construction and demolition waste (CDW) generated from building construction, renovation, demolition, site clearance, and excavation activities[3,4]. CDW typically consists of large, heavy debris such as bricks, concrete, timber, metals, plastics, plasterboard, glass, and cardboard, presenting considerable challenges in waste management and resource recovery[5,6]. Efficient management and valorisation of CDW are essential for minimising environmental impacts and promoting sustainable development, aligning with broader efforts in waste management[7].

CDW constitutes a significant waste stream in many countries, consuming around 40% of the total waste by weight[1]. For instance, it contributed 39% of solid waste across all sectors in Australia in 2022-2023[8] and 38.4% of total solid waste in Europe in 2022[9]. The improper management of CDW poses significant environmental challenges[10]. Landfilling CDW leads to extensive land degradation, loss of valuable landfill space, and increased greenhouse gas emissions due to the decomposition of organic materials and the energy-intensive production of new construction materials to replace discarded ones[11]. Additionally, the leaching of hazardous substances such as heavy metals, asbestos, and chemical additives from improperly disposed waste can contaminate soil and groundwater, posing risks to ecosystems and human health[12]. The extraction of virgin raw materials to meet construction demands further exacerbates deforestation, biodiversity loss, and carbon emissions, intensifying

[1]Department of Civil Engineering, Faculty of Engineering,Monash University, Melbourne, Australia. [2]Department of Data Science and AI, Faculty of IT, Monash University, Melbourne, Australia. [3]Civil Engineering Discipline, School of Engineering, Monash University, Subang Jaya, Malaysia. ✉e-mail: diani.sirimewan@monash.edu

climate change impacts[13]. In contrast, recycling and reusing CDW can significantly reduce these environmental burdens by conserving natural resources, lowering energy consumption, and mitigating pollution[14].

A significant portion of waste generated from large-scale construction and demolition projects is typically processed on-site or through off-site material recovery facilities (MRFs) to recover valuable materials[15]. However, mixed waste loads originating from minor construction and demolition projects are often sent directly to landfills[16]. This is primarily due to the challenges of handling mixed waste, which relies heavily on manual labour[17]. The manual sorting process is not only labour-intensive but also time-consuming and costly, making it less economically viable. Furthermore, manual waste handling is prone to occupational safety and health risks due to prolonged exposure to contaminated materials[18].

The implementation of automation at MRFs has emerged as a viable and effective approach to overcome the challenges in conventional waste handling[19]. Recent advancements in automated systems powered by artificial intelligence, deep learning, computer vision, and robotics offer promising solutions for efficient waste handling[20–23]. Deep learning models based on computer vision can analyse the visual attributes of mixed waste streams to recognise and categorise materials accurately[24]. Once these materials are identified, robotic systems can be deployed to perform sorting tasks[25]. Segmentation techniques are particularly crucial in this context, as they enable fine-grained waste recognition by providing spatial geometry and pixel-level information on the boundaries of waste materials[26]. Integrating such advanced technologies into MRF operations can significantly optimise the CDW management process. This can reduce the reliance on manual labour while improving safety and operational efficiency[7].

Recent studies have increasingly focused on leverage of computer vision-based deep learning models to identify and localise CDW by analysing their visual attributes through image data[21,26]. However, training such state-of-the-art models requires extensive, high-quality datasets to ensure robust and accurate performance across diverse scenarios[27]. These datasets must capture various visual features, environmental conditions, and object variations to enable models to generalise effectively for real-world applications[28]. Obtaining such datasets presents significant challenges. Collection of large volumes of labelled data is time-intensive. It often demands specialised expertise, particularly for complex tasks such as segmentation, which require detailed, pixel-level annotations[29]. Furthermore, securing access to diverse and representative data can be challenging, especially in domains like construction and demolition. These factors highlight the urgent need for collaborative efforts in dataset creation and advanced computer vision models to automate waste recognition that can be utilised in real-world applications. Table 1 provides a summary of most recent studies that have utilised computer vision models for segmentation and detection of CDW, along with details of the datasets used in those studies.

The datasets utilised in recent studies are diverse and captured from various perspectives and environments, offering varying levels of complexity and realism. Studies by Dong, *et al.*[15] and Driouache, *et al.*[30] employed datasets with images of truckloads containing construction waste captured from weigh bridges, providing a broader perspective on mixed and single waste streams. However, the datasets are not accessible for further reseach and applications. In contrast, several other studies used datasets with images of individual or small to medium-sized waste objects in lower to higher cluttered levels, often arranged on controlled or structured surfaces[28,31,32]. Additionally, some datasets focus on recycled materials with specific particle sizes[33], offering insights into fine-grained material handling but lacking the complexity of heterogeneous waste streams. While these datasets showcase a range of imaging conditions, there is a notable variation in their ability to replicate real-world scenarios. Datasets containing small or single waste objects on uniform backgrounds may simplify the task for computer vision models but fail to capture the details of mixed CDW typically encountered in practical scenarios.

This study employs a dataset named 'CDW-Seg'[34], specifically designed to overcome the limitations posed by the lack of publicly available datasets for the segmentation of CDW in-the-wild. CDW-Seg[34], comprising images of skip bins filled with CDW captured at authentic construction sites, represents the intricate and cluttered nature of real-world CDW scenarios. By addressing the challenges of class diversity, mixed material composition, and varying environmental conditions, CDW-Seg[34] provides a robust benchmark for training and evaluating advanced computer vision models.

Methods

Data sources. A comprehensive and high-quality dataset is essential for training computer vision models, enabling effective feature learning and generalisation to complex real-world scenarios[21]. However, publicly available datasets featuring CDW in authentic cluttered conditions are limited. This presents a significant challenge for developing automated waste recognition systems. To bridge this gap, we gathered 430 high-resolution images depicting skip bins filled with mixed CDW collected from diverse active construction sites. These images were captured at various active construction sites around Melbourne, Australia.

The images were deliberately captured from multiple angles, perspectives, and distances, including top-down, oblique, and side views, to represent the visual variability typically encountered in CDW scenarios. This diversity was incorporated to simulate the range of viewpoints that would be expected from CCTV and monitoring systems used at MRFs, where camera placement, orientation, and hardware can vary widely. The images were taken using a standard mobile phone camera, which provided flexibility in positioning and capturing images under various natural lighting conditions and backgrounds, adding to the dataset's practicality and applicability across different waste monitoring environments. This intentional variation enhances the potential of the dataset for training robust models suitable for deployment across a wide range of real-world MRF contexts.

The dataset focuses on skip bins and medium-range perspectives rather than full truckload views. This choice was made to capture detailed visual features of individual and overlapping waste materials, which are often not detectable from high-mounted surveillance systems. Such close-up imagery is particularly relevant for training models intended for applications in robotic sorting, stationary inspection stations, or drop-off points, where fine-grained, class-specific segmentation is critical.

Source	Methods	Nature of the dataset	Computer vision models
Dong, *et al.*[15]	Semantic segmentation	Images of construction waste truckloads captured from the perspective of a weigh bridge	CNNs, Attention modules, Transformers
Driouache, *et al.*[30]	Semantic segmentation	Images of dump trucks captured from the perspective of a weigh bridge	DeepLabv3+
Sirimewan, *et al.*[40]	Semantic segmentation	Images of CDW deposited skip bins captured at real construction sites	DeepLabv3+ and U-Net
Sirimewan, *et al.*[29]	Semantic segmentation	Images of CDW deposited skip bins captured at real construction sites	Adversarial dual-view networks
Wang, *et al.*[41]	Semantic segmentation	Images of construction waste collected from different sources/ synthetically generated images	Transformer-based architectures
Dong, *et al.*[26]	Semantic segmentation	Images of construction waste truckloads captured from the perspective of a weigh bridge	Transformer-based architecture
Lu and Chen[5]	Semantic segmentation	Images of construction waste truckloads captured from the perspective of a weigh bridge	DeepLabv3+
Sirimewan, *et al.*[17]	Prompt-guided segmentation	Images of CDW deposited skip bins captured at real construction sites	Segment Anything Model
Wu, *et al.*[33]	Instance segmentation	Images of recycled aggregates (particle size range 0 mm – 45 mm)	U-Net-based multi-star algorithm
Prasad and Arashpour[42]	Instance segmentation	Images of recyclable objects arranged on a flat, dark surface	Mask-RCNN-based fusion model
Prasad and Arashpour[28]	Instance segmentation	Images of recyclable objects arranged on a flat, dark surface	YOLO-seg versions and FastSAM
Prasad and Arashpour[43]	Instance segmentation	Images of recyclable objects arranged on a flat, dark surface	Mask-RCNN-based fusion model
Na, *et al.*[44]	Instance segmentation	Images of waste collected at dump site and through web scraping	YOLACT
Heo and Na[45]	Segmentation	Images of construction waste captured on different backgrounds	Segment Anything Model
Demetriou, *et al.*[32]	Object detection	Images of waste objects arranged on a conveyor belt	YOLOV8
Yang, *et al.*[31]	Object detection	Images of construction waste objects arranged on a structured surface	FE-YOLO
Demetriou, *et al.*[27]	Object detection	Images of waste objects arranged on a conveyor belt	SSD, YOLO, Faster-RCNN
Li, *et al.*[46]	Object detection	Images of CDW objects arranged on a conveyor belt	Mask-RCNN-based fusion model
Chen, *et al.*[7]	Object detection and sorting	Images of waste objectes arranged on a flat white surface	Morphology-based segmentation

Table 1. Recent studies on automated CDW recognition.

Data processing. Following data collection, a careful preprocessing step was performed to ensure dataset quality. Images that exhibited poor visual clarity or inadequate resolution were reviewed and excluded, leaving a refined set of high-resolution images (each 3000×4000 pixels) clearly capturing the boundaries and visual characteristics necessary for precise annotation. The dataset comprises 5,413 annotated waste objects, collectively covering a total pixel area of 2,492,021,189 pixels, distributed across ten distinct classes commonly encountered in CDW contexts. These include concrete, fill dirt, timber, hard plastic, soft plastic, steel, fabric, cardboard, plasterboard, and the skip bin itself. The classes were selected based on their prevalence and importance in construction and demolition activities.

To generate accurate ground-truth segmentation masks, manual annotation was performed using Labelme[35], an open-source annotation tool. This detailed and labor-intensive process involved carefully tracing polygons around the edges of individual waste materials within each image and assigning class-wise labels using distinct colours. Annotation of an individual image required an average of 25 minutes, highlighting the detailed effort invested to ensure the accuracy of annotations. Annotation was carried out following a semantic segmentation approach, which involves assigning each pixel within an image to a specific category label, thereby enabling detailed differentiation between individual waste materials and the background. Pixel-level masks generated through semantic segmentation provide precise ground-truth labels for each image, facilitating model training for accurate identification and localization of waste materials. The annotated categories reflect the typical composition of CDW, enhancing the relevance and applicability of the dataset for automated waste handling practices within the construction and demolition industry.

The annotated waste materials in these masks were represented using colour-coded regions corresponding to their assigned categories, as presented in Fig. 1. The unannotated areas were visually indicated in black. This colour-coding scheme enhanced the interpretability of the segmentation results, effectively distinguishing annotated categories from the unannotated regions. Figure 1 presents a sample of the CDW-Seg[34], including source images, corresponding ground-truths, description of classes and class distribution histograms. Following annotation, the dataset was partitioned into three subsets for training (75%), validation (15%), and testing (10%) to systematically facilitate the training, validation, and testing processes. This partitioning strategy ensures balanced data distribution across subsets, enhancing the robustness and generalisation capabilities of the trained model.

Data Record

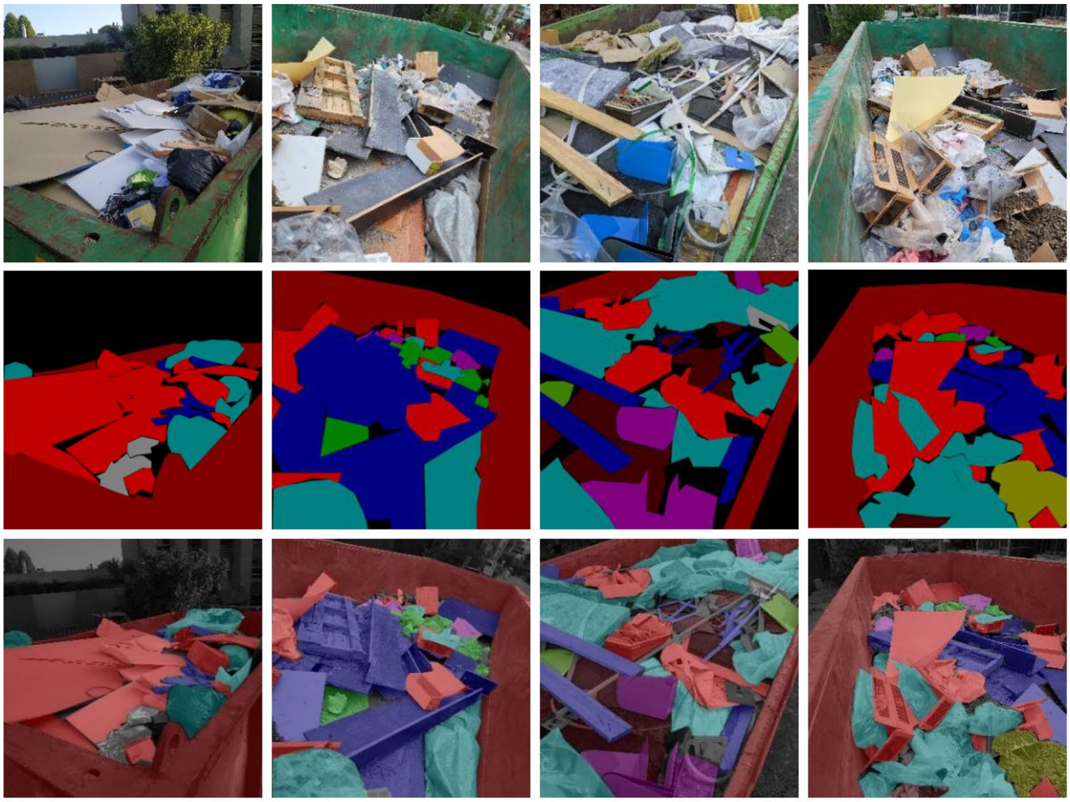
The CDW-Seg dataset is available at Figshare (https://doi.org/10.6084/m9.figshare.28573229)[34]. The dataset consists of three main folders: *Original_Images_and_Annotation_Files*, *Ground_Truths_VOC_Format* and *Ground_Truths_COCO_Format* as presented in Fig. 2. Since this study employs semantic segmentation, the ground-truth annotations are primarily provided in Pascal VOC format[36]. However, to enhance usability and facilitate further research, the dataset has also been converted into the COCO format[37]. The structured dataset ensures compatibility with various computer vision-based deep learning networks, supporting a wide range of segmentation tasks, including semantic segmentation and instance segmentation.

The *Original_Images_and_Annotation_Files* folder contains high-resolution images and their corresponding manually annotated JSON files. The *Ground_Truths_VOC_Format* folder includes subfolders for low-resolution

(a)

(b)

(c)



(d)

Class	Description	Colour
Concrete	Pieces of concrete/ mortar	
Fill dirt	Stone/ gravel/ aggregate/ rubble/ soil/ sand	
Timber	Wood/ timber (processed wood)/ chipboard	
Hard plastic	HDPE/ PVC	
Soft plastic	LDPE/ PET or PETE/ polystyrene	
Steel	Ferrous/ aluminium/ non-ferrous	
Fabric	Carpets/ cushions	
Cardboard	Anything made from cardboard and paper	
Plasterboard	Plasterboard or drywall	
Bin	Bin that collects and transports waste to MRFs	

(e)

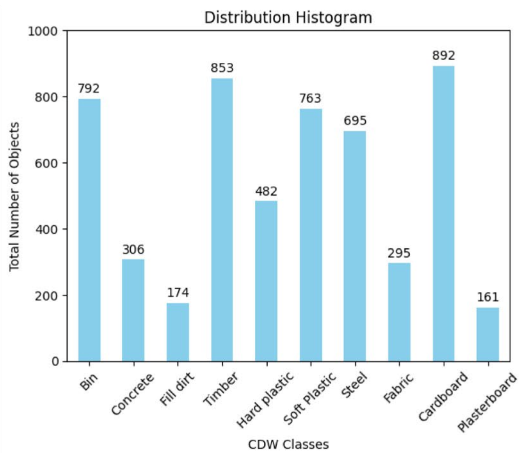


Fig. 1 Overview of the dataset. (**a**) source images, (**b**) ground-truths (**c**) ground-truths overlaid on source images (**d**) description of classes and (**e**) class distribution histogram.

images, semantic and instance segmentation masks, and visual overlays to support interpretability. The *Ground_Truths_COCO_Format* folder contains the same image set, overlay visualisations, and a comprehensive annotations.json file following the COCO standard. The availability of both Pascal VOC and COCO formats ensures that researchers can apply different deep learning architectures to the dataset, enhancing the scope of automated CDW recognition tasks.

Technical Validation

The CDW-Seg dataset[34] was developed to support high-quality, class-wise segmentation of CDW materials. We used a representative model architecture and evaluation pipeline to validate the utility and reliability of the dataset for training segmentation models as detailed below.

The recent studies have explored various deep learning architectures for CDW recognition including convolutional neural networks (CNNs) and transformer-based architectures. However, the potential of large-scale vision foundation models remains underexplored in this domain. Our technical validation focuses on demonstrating that the CDW-Seg dataset[34] is suitable for use with such models, particularly in resource-constrained environments like MRFs. We employed a fine-tuned version of the Segment Anything Model 2 (SAM2)[38] with

```
Dataset_Root
|
├── Original_Images_and_Annotation_Files
|   ├── High_Resolution_Images
|   ├── Manually_Annotated_JSON
|
├── Ground_Truths_VOC_Format
|   ├── JPEGImages
|   ├── SegmentationClassPNG
|   ├── SegmentationClassVisualization
|   ├── SegmentationObjectPNG
|   ├── SegmentationObjectVisualization
|
├── Ground_Truths_COCO_Format
|   ├── JPEGImages
|   ├── Visualization
|   ├── annotations.json
```

Fig. 2 Data repository structure.

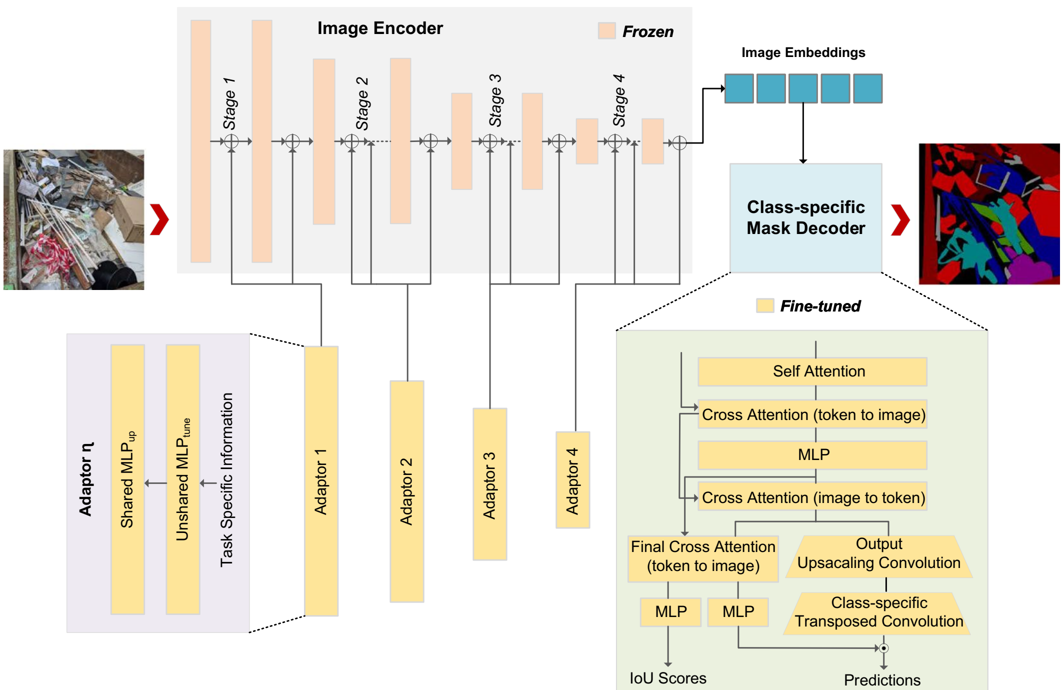


Fig. 3 Model architecture.

a hierarchical Vision Transformer (hiera-ViT)-based image encoder to validate the applicability of the dataset as illustrated in Fig. 3. The encoder which is pretrained on large-scale datasets, was kept frozen to preserve general visual features, while lightweight adapters were introduced in each stage for task-specific fine-tuning as illustrated in Fig. 3. The segmentation labels used for training and validation were sourced directly from the SegmentationClassPNG folder of the dataset in Pascal VOC format, which ensures consistency with the annotations described in the Data Records section.

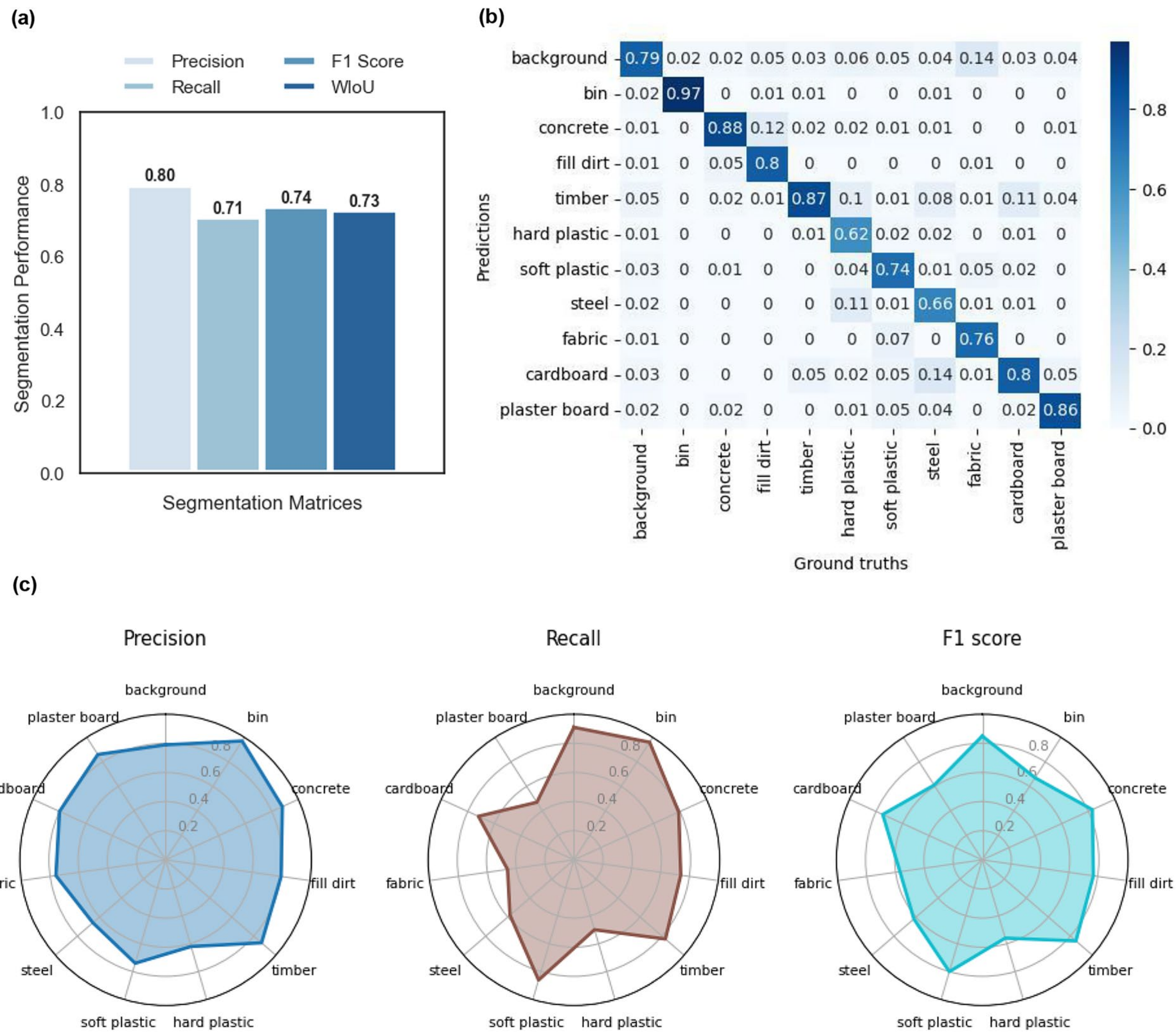


Fig. 4 (**a**) Mean segmentation performance, (**b**) confusion matrix and (**c**) class-wise segmentation performance in terms of precision, recall and F1-score values.

The dataset supports both semantic and instance segmentation tasks. Semantic segmentation masks were manually annotated using Labelme[35], assigning a unique class label to each pixel. This level of granularity enables the development of high-precision models, which we tested using standard evalution metrics. To assess annotation quality and segmentation consistency, we measured the precision (Eq. 1), recall (Eq. 2), F1-score (Eq. 3), and weighted intersection over union (WIoU) (Eq. 4) between the predicted and ground-truth masks. These metrics provide a robust evaluation of how well the dataset enables a model to learn accurate segmentation boundaries.

$$Precision = \frac{True\ Positives(TP)}{True\ Positives(TP) + False\ Positives(FP)} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1score = \frac{2TP}{2TP + FP + FN} \tag{3}$$

$$WIoU = \frac{1}{C} \cdot \frac{\sum_{c=1}^{C}(w_c \cdot TP_c)}{\sum_{c=1}^{C} w_c \cdot (TP_c + FP_c + FN_c)} \tag{4}$$

where c is the number of classes, w_c is the weight for each class, whereas TP_c, FP_c and FN_c are the true positives, false positives, and false negatives for class c, respectively.

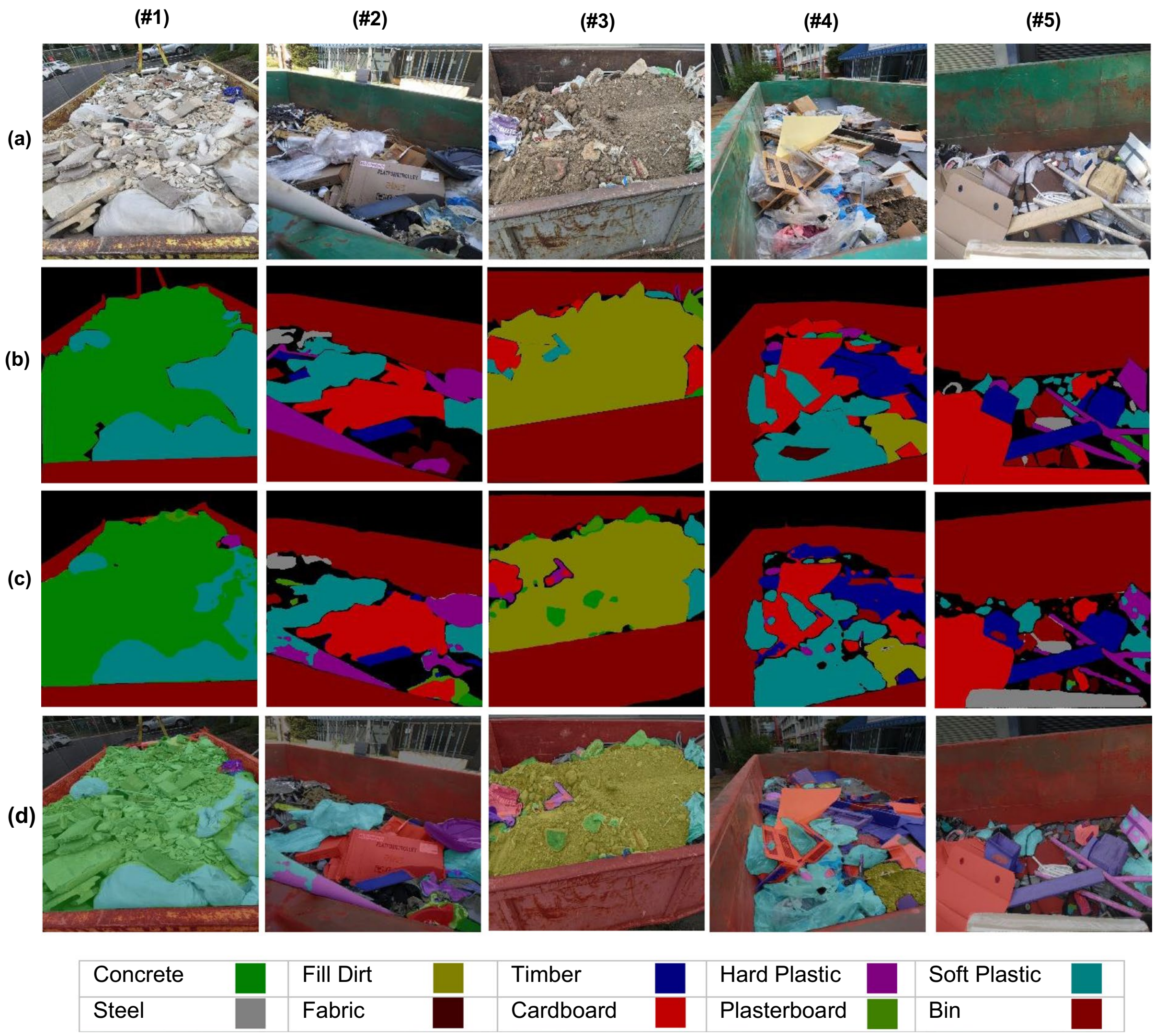


Fig. 5 Qualitative results of CDW segmentation (**a**) source images, (**b**) ground-truths, (**c**) predictions and (**d**) predictions overlaid on source images.

Quantitative analysis. Figure 4(a) presents the segmentation performance across the CDW-Seg dataset[34], with the model achieving a mean precision of 0.80 and a WIoU of 0.73. Classes such as concrete, timber, and plasterboard performed strongly, while fill dirt, cardboard, fabric, and soft plastic also achieved precision scores above 0.75. Lower precision was observed for steel and hard plastic, mainly due to their high variability in appearance. These results underscore how consistent visual features contribute to better segmentation accuracy, while variability in material characteristics can challenge the model's performance.

The confusion matrix in Fig. 4(b) highlights several class-wise misclassifications, reflecting the inherent complexity of CDW materials. Notable confusions include concrete vs. fill dirt (12%), hard plastic vs. steel (11%), and steel vs. cardboard (14%). These misclassifications can be attributed to overlapping visual features such as texture, colour, and surface finish. For instance, materials like glossy cardboard may look like steel, and timber and cardboard (11%) often share similar colour tones in dusty site conditions. These findings underscore the challenge of distinguishing between visually similar waste types, especially when materials are mixed or partially obscured. They also highlight the practicality of the dataset and suggest that future models may benefit from enhanced contextual feature extraction and data augmentation strategies. Figure 4(c) visualises segmentation performance across all classes.

Qualitative analysis. Figure 5 provides qualitative visualisations of the model's predicted segmentations, illustrating both its strengths and limitations. The model accurately segmented many CDW classes, confirming its ability to recognise and localise diverse waste materials. However, consistent with quantitative results, some misclassifications were observed. For instance, confusion between fill dirt and concrete (sample #3) due to overlapping aggregate features, and between glossy cardboard and steel (sample #5) because of similar surface textures. These examples reflect the visual complexity of CDW in real-world settings and highlight the need for further refinement in handling material variability and inter-class similarities.

Computational effciency. The proposed model uses the hiera-ViT-large encoder with an adapter-based fine-tuning strategy to enhance computational efficiency. This results in reducing the number of trainable parameters from 225.4 million to 3.94 million, which is approximately 1.75% of the total model size. This approach preserves the encoder's pre-trained semantic features while enabling task-specific learning for CDW segmentation. It significantly lowers the computational resources including high memory and processing power, making the model suitable for semantic segmentation tasks in resource-constrained environments such as MRFs, without compromising the performance.

Usage Notes

The dataset includes original high-resolution images, manually annotated segmentation masks, and corresponding ground-truth annotations created using Labelme[35] (https://github.com/wkentaro/labelme). The annotations provide semantic segmentation labels, enabling detailed class-wise recognition of CDW. This dataset can be utilised in computer vision-based deep learning models for automated waste classification and segmentation tasks. Additionally, the structured annotations support further research in deep learning-based waste recognition and can be extended to real-time waste handling applications.

Code availability

The code was implemented in Python using PyTorch[39] framework for training and evaluating the segmentation models on the CDW-Seg dataset[34]. The code is publicly available at: https://github.com/DianiSirimewan/SAM2-Adapter-CDW.

Received: 13 March 2025; Accepted: 20 May 2025;
Published online: 28 May 2025

References

1. Yuan, L., Yang, B., Lu, W. & Peng, Z. Carbon footprint accounting across the construction waste lifecycle: A critical review of research. *Environ. Impact Assess. Rev.* **107**, 107551, https://doi.org/10.1016/j.eiar.2024.107551 (2024).
2. Arashpour, M. AI explainability framework for environmental management research. *J. Environ. Manage.* **342**, 118149, https://doi.org/10.1016/j.jenvman.2023.118149 (2023).
3. Lee, S., Chang, H. E. & Lee, J. Construction and demolition waste management and its impacts on the environment and human health: moving forward sustainability enhancement. *Sustain. Cities Soc.*, 105855 https://doi.org/10.1016/j.scs.2024.105855 (2024).
4. Guven, G. *et al*. A construction classification system database for understanding resource use in building construction. *Sci. Data* **9**, 42, https://doi.org/10.1038/s41597-022-01141-8 (2022).
5. Lu, W. & Chen, J. Computer vision for solid waste sorting: A critical review of academic research. *Waste Manag.* **142**, 29–43, https://doi.org/10.1016/j.wasman.2022.02.009 (2022).
6. Zbíral, T. & Nežerka, V. Computer Vision-Based Algorithms for Recognition of Construction and Demolition Waste Materials. *Adv. Sci. Technol.* **133**, 11–17, https://doi.org/10.1016/j.eiar.2024.107551 (2023).
7. Chen, J., Fu, Y., Lu, W. & Pan, Y. Augmented reality-enabled human-robot collaboration to balance construction waste sorting efficiency and occupational safety and health. *J. Environ. Manage.* **348**, 119341, https://doi.org/10.1016/j.jenvman.2023.119341 (2023).
8. NWRRR. National waste and resource recovery report. https://www.dcceew.gov.au/environment/protection/waste/publications/national-waste-resource-recovery-reporting (2024).
9. *European Commision Waste Statistics* https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Waste_statistics (2022).
10. Lin, S., Huang, L., Liu, X., Chen, G. & Fu, Z. A construction waste landfill dataset of two districts in Beijing, China from high resolution satellite images. *Sci. Data* **11**, 388, https://doi.org/10.1038/s41597-024-03240-0 (2024).
11. Munir, Q., Lahtela, V., Kärki, T. & Koivula, A. Assessing life cycle sustainability: A comprehensive review of concrete produced from construction waste fine fractions. *J. Environ. Manage.* **366**, 121734, https://doi.org/10.1016/j.jenvman.2024.121734 (2024).
12. Wang, L., Zhu, Z., Xie, X. & Wu, J. Research trends in the treatment and recycling of construction and demolition waste based on literature data-driven visualization. *J. Environ. Manage.* **371**, 123018, https://doi.org/10.1016/j.jenvman.2024.123018 (2024).
13. Zhang, C., Dong, H., Geng, Y., Liang, H. & Liu, X. Machine learning based prediction for China's municipal solid waste under the shared socioeconomic pathways. *J. Environ. Manage.* **312**, 114918, https://doi.org/10.1016/j.jenvman.2022.114918 (2022).
14. Zhao, W., Hao, J. L., Gong, G., Fischer, T. & Liu, Y. Applying digital technologies in construction waste management for facilitating sustainability. *J. Environ. Manage.* **373**, 123560, https://doi.org/10.1016/j.jenvman.2024.123560 (2025).
15. Dong, Z., Yuan, L., Yang, B., Xue, F. & Lu, W. Benchmarking computer vision models for automated construction waste sorting. *Resour. Conserv. Recycl.* **213**, 108026, https://doi.org/10.1016/j.resconrec.2024.108026 (2025).
16. Ranjbar, I., Ventikos, Y. & Arashpour, M. Deep learning-based construction and demolition plastic waste classification by resin type using RGB images. *Resour. Conserv. Recycl.* **212**, 107937, https://doi.org/10.1016/j.resconrec.2024.107937 (2025).
17. Sirimewan, D., Kunananthaseelan, N., Raman, S., Garcia, R. & Arashpour, M. Optimizing waste handling with interactive AI: Prompt-guided segmentation of construction and demolition waste using computer vision. *Waste Manag.* **190**, 149–160, https://doi.org/10.1016/j.wasman.2024.09.018 (2024).
18. Lu, W., Chen, J. & Xue, F. Using computer vision to recognize composition of construction waste mixtures: A semantic segmentation approach. *Resour. Conserv. Recycl.* **178** https://doi.org/10.1016/j.resconrec.2021.106022 (2022).
19. Chen, X., Huang, H., Liu, Y., Li, J. & Liu, M. Robot for automatic waste sorting on construction sites. *Autom. Constr.* **141** https://doi.org/10.1016/j.autcon.2022.104387 (2022).
20. Sun, Y. & Gu, Z. Using computer vision to recognize construction material: A Trustworthy Dataset Perspective. *Resour. Conserv. Recycl.* **183**, 106362, https://doi.org/10.1016/j.resconrec.2022.106362 (2022).
21. Wu, T.-W., Zhang, H., Peng, W., Lü, F. & He, P.-J. Applications of convolutional neural networks for intelligent waste identification and recycling: A review. *Resour. Conserv. Recycl.* **190**, 106813, https://doi.org/10.1016/j.resconrec.2022.106813 (2023).
22. Chen, F. *et al*. Vision-based sorting in mixed food-inorganic waste stream. *Resour. Conserv. Recycl.* **212**, 107964, https://doi.org/10.1016/j.resconrec.2024.107964 (2025).
23. Zhang, Q. *et al*. Recyclable waste image recognition based on deep learning. *Resour. Conserv. Recycl.* **171**, 105636, https://doi.org/10.1016/j.resconrec.2021.105636 (2021).
24. Zhang, Q. *et al*. A multi-label waste detection model based on transfer learning. *Resour. Conserv. Recycl.* **181**, 106235, https://doi.org/10.1016/j.resconrec.2022.106235 (2022).
25. Dodampegama, S., Hou, L., Asadi, E., Zhang, G. & Setunge, S. Revolutionizing construction and demolition waste sorting: Insights from artificial intelligence and robotic applications. *Resour. Conserv. Recycl.* **202**, 107375, https://doi.org/10.1016/j.jenvman.2021.114405 (2024).
26. Dong, Z., Chen, J. & Lu, W. Computer vision to recognize construction waste compositions: A novel boundary-aware transformer (BAT) model. *J Environ Manage* **305**, 114405, https://doi.org/10.1016/j.jenvman.2021.114405 (2022).

27. Demetriou, D. *et al*. Real-time construction demolition waste detection using state-of-the-art deep learning methods; single–stage vs two-stage detectors. *Waste Manag.* **167**, 194–203, https://doi.org/10.1016/j.wasman.2023.05.039 (2023).
28. Prasad, V. & Arashpour, M. Real-time instance segmentation of recyclables from highly cluttered construction and demolition waste streams. *J. Environ. Manage.* **372**, 123365, https://doi.org/10.1016/j.jenvman.2024.123365 (2024).
29. Sirimewan, D., Harandi, M., Peiris, H. & Arashpour, M. Semi-supervised segmentation for construction and demolition waste recognition in-the-wild: Adversarial dual-view networks. *Resour. Conserv. Recycl.* **202**, 107399, https://doi.org/10.1016/j.resconrec.2023.107399 (2024).
30. Driouache, Y., Milpied, J. & Motamedi, A. Vision-based method to identify materials transported by dump trucks. *Eng. Appl. Artif. Intell.* **135**, 108768, https://doi.org/10.1016/j.engappai.2024.108768 (2024).
31. Yang, Y., Li, Y. & Tao, M. FE-YOLO: A Lightweight Model for Construction Waste Detection Based on Improved YOLOv8 Model. *Buildings* **14**, 2672, https://doi.org/10.3390/buildings14092672 (2024).
32. Demetriou, D., Mavromatidis, P., Petrou, M. F. & Nicolaides, D. CODD: A benchmark dataset for the automated sorting of construction and demolition waste. *Waste Manag.* **178**, 35–45, https://doi.org/10.1016/j.wasman.2024.02.017 (2024).
33. Wu, X., Kroell, N. & Greiff, K. Deep learning-based instance segmentation on 3D laser triangulation data for inline monitoring of particle size distributions in construction and demolition waste recycling. *Resour. Conserv. Recycl.* **205**, 107541, https://doi.org/10.1016/j.resconrec.2024.107541 (2024).
34. Sirimewan, D., Dayarathna, S., Raman, S., Bai, Y. & Arashpour, M. A benchmark dataset for class-wise segmentation of construction and demolition waste in cluttered environments. https://doi.org/10.6084/m9.figshare.28573229 (2025).
35. Wada. Labelme. https://github.com/wkentaro/labelme (2021).
36. Everingham, M., Van Gool, L., Williams, C. K., Winn, J. & Zisserman, A. The pascal visual object classes (voc) challenge. *Int. J. Comput. Vis.* **88**, 303–338, https://doi.org/10.1007/s11263-009-0275-4 (2010).
37. Lin, T.-Y. *et al.* Microsoft coco: Common objects in context. *Computer vision–ECCV 2014. Lecture Notes in Computer Science*, 740-755 https://doi.org/10.1007/978-3-319-10602-1_48 (2014).
38. Ravi, N. *et al.* Sam 2: Segment anything in images and videos. https://arxiv.org/abs/2408.00714 (2024).
39. Paszke, A. *et al.* Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems* **32** (2019).
40. Sirimewan, D. *et al.* Deep learning-based models for environmental management: Recognizing construction, renovation, and demolition waste in-the-wild. *J. Environ. Manage.* **351**, 119908, https://doi.org/10.1016/j.jenvman.2023.119908 (2024).
41. Wang, X. *et al*. Transformer-based automated segmentation of recycling materials for semantic understanding in construction. *Autom. Constr*. **154** https://doi.org/10.1016/j.autcon.2023.104983 (2023).
42. Prasad, V. & Arashpour, M. Optimally leveraging depth features to enhance segmentation of recyclables from cluttered construction and demolition waste streams. *J. Environ. Manage.* **354**, 120313, https://doi.org/10.1016/j.jenvman.2024.120313 (2024).
43. Prasad, V. & Arashpour, M. ShARP-WasteSeg: A shape-aware approach to real-time segmentation of recyclables from cluttered construction and demolition waste. *Waste Manag.* **195**, 231–239, https://doi.org/10.1016/j.wasman.2025.02.006 (2025).
44. Na, S., Heo, S., Han, S., Shin, Y. & Lee, M. Development of an Artificial Intelligence Model to Recognise Construction Waste by Applying Image Data Augmentation and Transfer Learning. *Buildings* **12** https://doi.org/10.3390/buildings12020175 (2022).
45. Heo, S. & Na, S. Developing WasteSAM: A novel approach for accurate construction waste image segmentation to facilitate efficient recycling. *Waste Manag. Res.*, 0734242X241290743 https://doi.org/10.1177/0734242X241290743 (2024).
46. Li, J. *et al.* RGB-D fusion models for construction and demolition waste detection. *Waste Manag.* **139**, 96–104, https://doi.org/10.1016/j.wasman.2021.12.021 (2022).

Acknowledgements

The authors are grateful for the support from the ASCII Lab (https://www.monash.edu/ascii) members at Monash University and their constructive feedback on progressive iterations of this work.

Author contributions

Diani Sirimewan: Conceptualisation, Writing - Original Manuscript, Investigation, Data Curation, Methodology, Software, Visualisation, Formal Analysis. Sanuwani Dayarathna - Methodology, Software, Writing – Review and Editing. Sudharshan Raman - Project Administration, Funding Acquisition, Yu Bai - Funding Acquisition, Supervision. Mehrdad Arashpour – Conceptualisation, Supervision, Project Administration, Funding Acquisition, Data Curation, Writing – Review and Editing.

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to D.S.