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VISION-BASED AUTOMATED WASTE QUANTIFICATION IN CONSTRUCTION SITES

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Abstract

Solid waste generated from construction activities poses serious environmental challenges and adversely affects the sustainability of the construction industry. Advancements in data-driven approaches, including computer vision (CV), offer a potential approach to automating the process of waste quantification on construction sites. This study proposes a system that utilises CV to quantify waste generated onsite. The proposed framework consists of the analysis of video streams of a waste container and estimating the waste material based on predefined waste categories. This study advances automated construction waste detection and identification and ultimately promotes efficient construction waste management, circular economy, and sustainable development.

Introduction

Vision-based systems have gained traction recently as essential tools to capture data at construction sites. These systems leverage image processing and computer vision to provide in-depth contextual analysis of the construction environment for multiple purposes, including construction progress monitoring, quality control, operation analysis, and safety monitoring (Omar et al., 2018; Martinez et al., 2019; Reja et al., 2022). One area that has been recently explored and could provide attractive benefits to the sustainability of construction operations is the use of cameras to identify and segregate construction waste (Tahir et al., 2024). Construction waste refers to the solid waste generated from construction, demolition, and renovation activities (Kofoworola & Gheewala, 2009).

The significant amount of waste produced during construction activities, estimated to account for 10-30% of all global solid waste, poses serious environmental challenges (Osmani, 2011). Waste reduction in the construction industry is key for any country aiming to achieve the UN sustainability goals marked for 2030, especially around sustainable consumption and production patterns (UN SDG #12). Current efforts have managed to divert about 13% of construction waste from landfills, looking for alternative ways of disposal or finding novel uses for certain materials found in construction waste (Harris, 2023). However, that is still far from the 99% goal set up for the near future as part of the Zero Waste to Landfill strategy. This strategy enhances waste diversion and aversion from primary sources and has surfaced as an integral part of circularity (Shukla & Khan, 2022).

Construction waste typically includes wood, metals, concrete, bricks, tiles, plastics, textiles, cardboard, and mixed materials such as drywall. By implementing effective construction waste management (CWM) strategies that comply with regulatory requirements, the impact of waste can be mitigated, and the overall sustainability of construction practices can be enhanced. This starts by transforming current approaches from waste estimates relying on BIM methodologies (Quiñones et al., 2022) to more data-driven methods utilising real-time site data.

Incorporating automated systems for waste quantification on-site contributes to environmental sustainability and supports contractors in optimising material usage and enhancing their competitive edge in the market (Ranjbar et al., 2025). Efficient CWM practices can lead to cost savings, improved compliance with local and federal regulations, and strengthened relationships with stakeholders, ultimately fostering a reputation for sustainability within the construction industry. Although most material and process decisions have already been decided by the construction phase, the effectiveness of any waste reduction strategy is not confirmed until the end of the project. By then, most sustainability and circularity efforts cannot fully be understood and evaluated due to a lack of detailed waste data. Currently, waste reduction is considered successful if total waste weight is reduced, limited by current data available. With no information on the waste composition, there is limited understanding on the real impact of waste management strategies that should move from weight focused approaches to value-based approaches.

This paper proposes the use of cameras to monitor waste cumulation points in construction sites, e.g., skips, and the use of artificial intelligence approaches to derive quantities of waste accumulated based on waste type classifications. The proposed system aims to provide enough data and information about waste generation in construction projects to relevant stakeholders in a way that emphasises the value of construction waste and changes the way construction tackles the circular economy from its site waste.

State of the art

Construction waste management and quantification have garnered significant attention due to the environmental and economic impacts associated with construction and demolition activities. Effective CWM strategies are essential to mitigate these impacts, and accurate quantification methods are crucial for implementing such strategies. Traditional quantification methods on construction sites often involve direct measurement techniques. As noted by Maniam et al. (2018), these methods are typically categorised into "soft" and "hard" measures. Hard measures encompass visual inspections, tape measurements, and truckload records and have been the cornerstone for providing estimates on waste generation during construction projects.

Advancements in technology have introduced more sophisticated approaches to waste quantification and sorting. Dong et al. (2025) conducted a systematic and comprehensive benchmarking study to compare the accuracy, efficiency, and robustness of seventeen computer-vision models used for automated construction waste sorting. Building information modelling (BIM) has emerged as a valuable tool in this context. Quiñones et al. (2022) presented a software application called WE-BIM, integrated into Autodesk Revit, which enables real-time quantification of construction waste during the design phase. This tool uses a validated waste quantification model aligned with the European List of Waste, allowing designers to simulate and compare different design alternatives to minimise waste effectively. Similarly, machine learning techniques have enhanced waste quantification methods. According to Akambi et al. (2024), an integrated BIM and machine learning system can predict the circularity of construction and demolition waste. By analysing a dataset of 2,280 demolition projects, the study employed the XGBoost model, achieving high accuracy in predicting waste quantities. This integration supports circular economy initiatives by providing insights into the recyclability of waste.

In the context of high-rise buildings, accurate waste quantification models are essential due to the scale and complexity of such projects. Viswalekshmi et al. (2024) proposed a model to estimate the waste generation index (WGI) for high-rise residential buildings in India. This model, validated through a case study of an 18-story building, found that concrete, aggregates, and blocks account for 92% of the total waste generated. Models like these are instrumental in establishing regional construction waste databases and formulating targeted CWM strategies. Additionally, regulatory measures and economic incentives play a crucial role in waste management. The European Union emphasises recycling building materials and adopting cradle-to-grave ideologies in construction practices. The EU Construction & Demolition Waste Management Protocol highlights benefits beyond financial gains, such as job creation and reduced landfilling. Taxation strategies, such as landfill taxes implemented in countries like Belgium, Denmark, and Austria, have effectively reduced landfill disposal and increased recycling rates (Kaza et al., 2018).

Although straightforward, these methods can be labour-intensive and lack precision due to their reliance on manual data collection, subjective assessments, and pre-construction estimations. Literature has suggested that estimates have a meaningful value for pre-design and design stages; however, more accurate quantifications should be done on-site (Bakchan et al., 2019). During the construction phase, waste estimations are rarely evaluated, and final actual waste quantities remain unknown during this phase. Timely segregation on site is key to reducing waste to landfills and enabling circularity. However, quantification to determine volume and potential value that supports decision-making is also necessary. Indeed, most quantifications are done after the project is completed, as waste removal services charge based on waste weight, leaving segregation and recycling efforts with an unknown outcome and efficiency.

In summary, the literature highlights the need for a waste quantification process that not only looks at the total waste generated but also provides a more in-depth analysis. Compared to current approaches, that focus either on prior estimation from design or posterior analysis through big data, this paper aims to provide on-going waste generation data. When and what is generated is key information that would enable waste reduction strategies that could tackle current inefficiencies on sites properly. The system presented in this paper aims to provide a cost-effective and accurate solution to such challenges, being an enabler of more data-driven waste reduction and circular economy approaches. The system will aim to provide data with an accuracy in the range of ±10%, similar to the current estimates used in waste management facilities (Lu et al., 2021).

Methodology

Design science research (DSR) is a structured methodology often applied to develop innovative solutions to complex problems (Hevner et al., 2010). This project uses DSR to create a novel decision-support tool for sustainable construction waste management. This begins with problem identification through a literature review followed by iterative artifact design and prototyping. The artifact then would be rigorously evaluated in real-world construction scenarios to test its efficiency and practicality. Findings would inform refinements, and the final artifact would integrate predictive analytics to optimise waste reduction strategies, aligning with circular economy principles. The DSR approach has been successfully implemented in prior research as a bridge between theory and practice (Holmström et al., 2009).

This paper discusses the initial development of the artifact, a waste quantification system based on computer vision, and the initial proof of concept using actual data from construction sites. The proposed system will be presented in a schematic form within a clear framework, and then its predictive performance will be tested beyond the training dataset used. The test data comes from a residential project in the Northeast of England.

Framework

The proposed system works under the premise that construction site waste ends up in collection points with a varying degree of mix. Therefore, this waste is representative of the waste materials created by construction operations when they are thrown into the collection point (evidently slightly later). The waste management process outside the collection point is not monitored (manual or semi-manual, i.e. using loaders) considering current data protection laws.

As such, a single monocular camera is placed on top of the waste collection point, usually a skip or container, providing a clear top image of what it contains. The data is then stored (locally or in the cloud), processed, and analysed to quantify the current waste at the collection point. The focus is to determine the percentage of different wastes in the waste mix and their weights. A flowchart of the proposed framework is depicted in Figure 1.

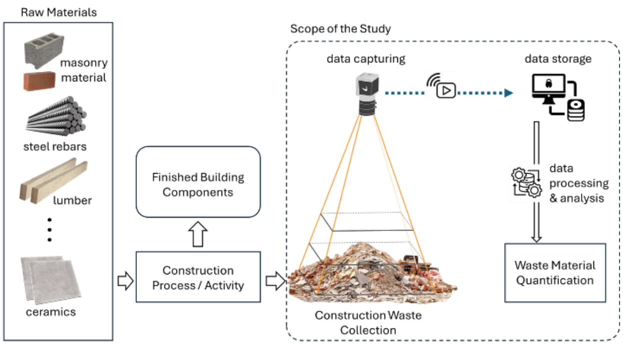

Figure 1: Proposed system framework for automated quantification of waste in construction sites.

Waste Capturing System

As stated in the previous section, a single monocular camera serves as the only input to the system. The positioning of the camera has a few design constraints that require mentioning. Those can be identified in Figure 2.

First, sufficient clearance is necessary for skips or containers in construction sites to be replaced from their site location. The camera shall be placed high enough to guarantee the systems' hardware integrity during these operations. Usually, skips are loaded and unloaded from trucks, requiring that clearance to be quite important. For example, in this study, 8-yard skips were used, and the clearance given was 5.5m from the ground.

Second, the camera is lifted above the ground with a temporary structure made of aluminium profiles. Given the design, one would want to keep the structure as small as possible by placing it as close as possible to the skip; however, one must account for the fact that the structure will block access to the skip for site equipment from at least one side.

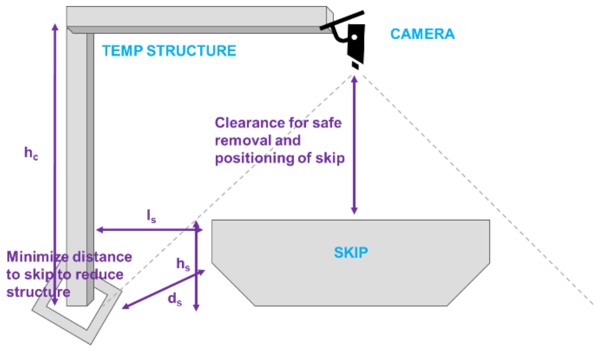

Figure 2: Schematics of the system's site installation requirements.

It is recommended that the last element to be fixed in this system is the lens, as it will depend on the constraints mentioned above. The system is flexible enough not to achieve a perfect top view; in fact, a slightly oblique view may help simplify the design and its installation on site. Finally, it is essential to note that the field of view from the camera must be larger (empirically >20%) than the skip area from the top, as loading and unloading of skips or containers are not precise operations. The system should be flexible enough to handle container localisation and orientation deviations. As a last resort, the camera could be panned to recalibrate the container location or the structure moved to accommodate lateral deviations.

System Algorithm

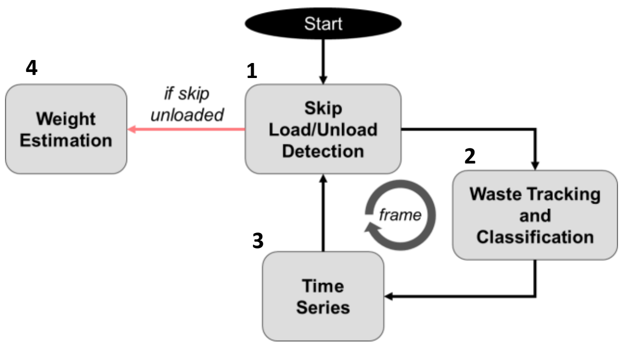

Figure 3: Flowchart diagram of the algorithm logic to output weight estimation.

The proposed system is built on three sequential modules executed on each captured frame and one module for weight estimation computed only after a skip has been unloaded (removed from the field of view). A flowchart specifying the system algorithm logic from its image input to the final weight estimation is presented in Figure 3. The algorithm loops over each frame of the video, tracking and classifying waste until the skip is removed, which triggers the weight estimation. The following subsections briefly describe the modules mentioned above.

Skip Load/Unload Detection

This module requires identifying when a container or skip appears or leaves the field of view. When a container becomes visible, the waste tracking and classification module is triggered, enabling the system to separate the results by each skip identified. This is achieved using image processing techniques of background subtraction and a binary mask obtained through threshold filtering and Gaussian blur. This approach is common for quickly identifying elements introduced into a static background with little computational cost (Bustos et al., 2023). In this case, this module identifies when a skip enters or exits the field of view of the camera. An example of the result of this module is illustrated in Figure 4.

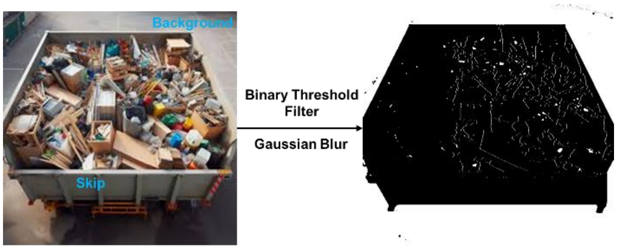

Figure 4: Sample image of a skip through background subtraction and binary filtering.

Looking at the final binary mask, the resulting image allows for determining if a skip has appeared or has left the field of view. Following equation 1, taking the average pixel value, $\boldsymbol{\overline{p}(x.y)}$, across the image and comparing it to a set threshold allows to determine if the skip is present ($\boldsymbol{s = 1}$) or not ($\boldsymbol{s = 0}$).

$$\boldsymbol{s = \overline{p}(x.y) < 0.9} \qquad (1)$$

Once the variable ($\boldsymbol{s}$) turns non-zero, the following modules that quantify waste in the skip are triggered; otherwise, calculations on this frame are finished.

Waste Tracking and Classification

Once a skip is detected in sight, this module aims to track and classify the waste being thrown into the skip. Going frame by frame, a YOLOv8 model is trained on classifying and locating the different classes of waste for construction and demolition as identified in the UK waste classification code (#17), also known as the List of Waste (LoW) or the European Waste Catalogue (EWC). This contains a total of 38 different classes of waste across all the different materials commonly used on construction sites (Gov UK Technical Guidance WM3).

As the system aims to quantify the waste generated, each detection needs to be tracked individually to avoid duplication of waste identified in the skip. For this, optical flow estimates are used to keep track of waste while on sight (Ilg et al., 2017). The quantification algorithm ignores tracked elements once added to the detection list. However, this poses an issue with over-accumulation of tracked elements as the skip gets full, becoming an impossible computational task for a standalone system (as designed).

As detections are only necessary once, a solution is envisioned based on motion. Once waste thrown into the skip settles, it lacks motion that can be easily detected through image processing methods. The system then stops tracking elements as they lose motion. This motion detection is performed by frame differentiation, a simple image processing technique that creates a mask by subtracting the pixel value of two consecutive images. Using the mask results, both the tracker and the AI model run on a filtered image that limits the tracking and detection/classification of moving objects. An example is given in Figure 5.

Figure 5: Example of tracking and detection of waste on a waste collection container.

Time Series

Once detections are accurately achieved, detections are stored across the sequence of frames to obtain a time series of detections per class. Note that the time series variables presented are discrete, not continuous, with data points obtained at the framerate of the camera. This means that for each waste class ($\boldsymbol{w}$), there are two sets of time series variables: ($\boldsymbol{D_w}$) that lists the number of detections for each class over time; and ($\boldsymbol{A_w}$) the area of the bounding box for each detection on each class. Standard camera calibration is required for the area to be in real units instead of square pixels. Both variables exist for each container or skip that is detected. Once the data is stored, the system goes to the next frame.

Weight Estimation

The weight estimation is obtained from the cumulative volume of each waste class when multiplied by its bulk density (see equation 2). Bulk density ($\boldsymbol{Bd_w}$), also called apparent density, is a material property defined as the mass of the many particles of the material divided by the bulk volume ($\boldsymbol{Bv_w}$).

$$\boldsymbol{W_w = Bd_w Bv_w} \qquad (2)$$

The bulk density of construction waste has been investigated recently in a way that simplifies waste analysis and enables big data approaches (Lu et al., 2021). The values for the bulk density of all classes can then be obtained from the available literature. Bulk volume is estimated assuming that all waste is of prismatic origin. This assumption runs from the base that all detections obtained have a base area ($\boldsymbol{A_w}$) based on their rough shape and orientation, and only their height ($\boldsymbol{h}$) remains as a variable to turn the area detected into a volume.

$$\boldsymbol{Bv_w} = \boldsymbol{A_w h} \tag{2}$$

Thus, the weight composition of the skip ($\%\boldsymbol{W_s}$), in relation to the waste thrown into it, would be:

$$\%\boldsymbol{W_w} = \frac{\boldsymbol{W_w}}{\sum \boldsymbol{W_w}} = \frac{\boldsymbol{Bd_w A_w h}}{\sum \boldsymbol{Bd_w A_w h}} = \boldsymbol{r}\frac{\boldsymbol{Bd_w A_w}}{\sum \boldsymbol{Bd_w A_w}} \tag{4}$$

Where the only incognita is the ratio of the waste height compared to the sum of all the waste heights ($\boldsymbol{r}$), the remaining terms are either constant or relate directly to the model outputs. This ratio of heights is assumed to be similar to another ratio we have information on, as stated in equation 5.

$$\boldsymbol{r} = \frac{\boldsymbol{D_w}}{\sum \boldsymbol{D_w}} \approx \frac{\boldsymbol{h}}{\sum \boldsymbol{h}} \tag{5}$$

Results

The system is tested on a construction site in Northern England. No information on the current site activities is known, and there is no information on the waste stream or management activities before dumping on waste collection points. The results showcased are not representative of project waste management approaches or waste generation across the project.

Two cameras are installed over two waste collection points and uninterruptedly record for 4 days. In total, waste data from 4 skips is collected. From that dataset, out of the 38 different waste types possible, only seven types per the UK LoW, are observed: glass (waste code: 17-02-02), brick (waste code: 17-01-02), metal (waste code: 17-04-07), plastic (waste code: 15-01-02), wood (waste code: 17-02-01), insulation (waste code: 17-06-04), and ceramic (waste code: 17-01-03).

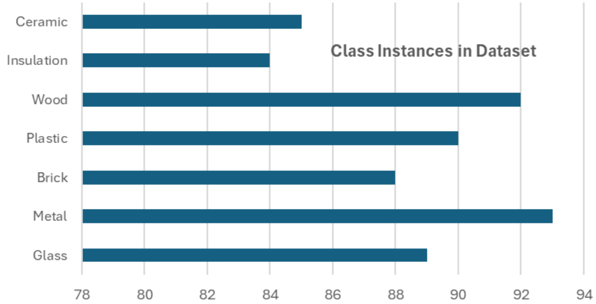

Figure 6: Dataset class instances used during the model training.

From the dataset, 438 images are labelled on those seven waste types, aiming for a balanced dataset across all classes. Figure 6 presents the dataset distribution across the 7 classes, showcasing the balancing approach taken to create the training dataset. A YOLOv8 pre-trained model on the COCO dataset is used and transfer learning approaches are leveraged to minimise the dataset quantity requirements. The average F1-score for all classes achieved is 0.74. As the number of images processed to obtain the weight composition of the skips is very large (e.g., skip 3 is filled over 41h of video), class detection accuracy does not need to be extremely accurate to obtain decent estimations. It is assumed that inaccuracies in both detection (false positives and negatives), classifications, and bounding box regression compensate for its variability (assuming Gaussian distribution of error).

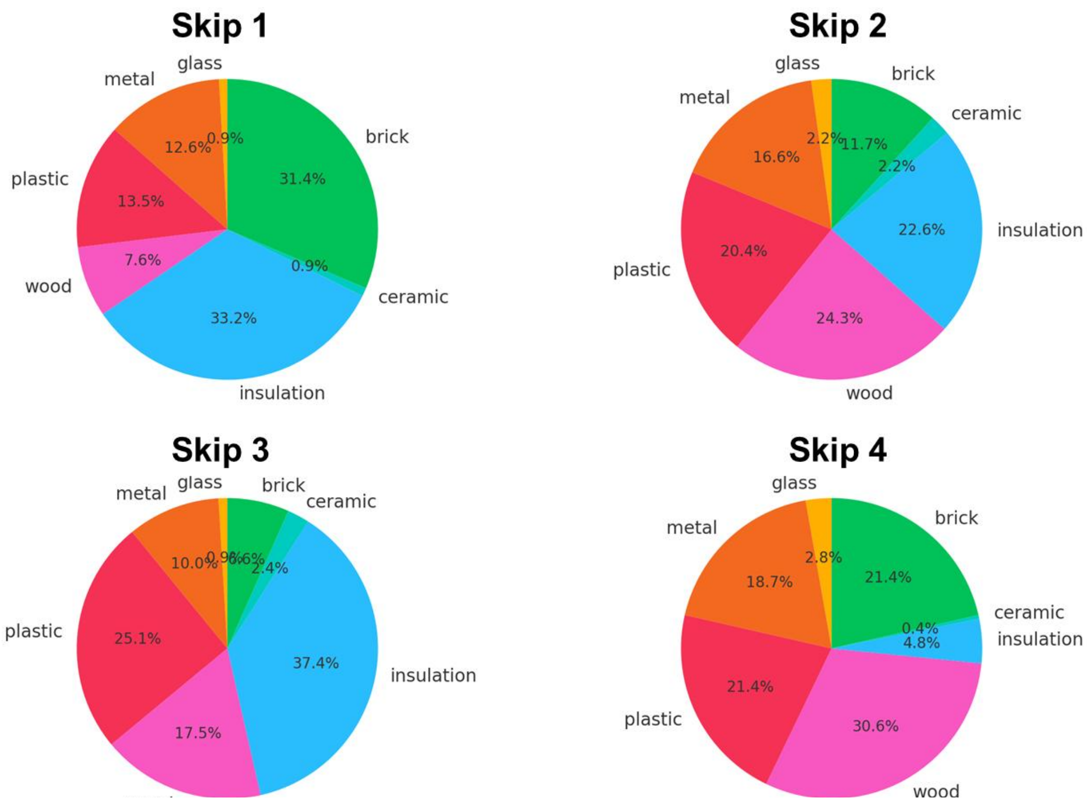

Figure 7: Pie chart of the weight estimation per skip.

The results of the weight estimation are presented in Figure 7. The system is able to independently compute waste compositions based on the estimated weight for all the skips. The system outputs are consistent with the equations stated in the previous section. To evaluate the system results from an accuracy perspective, manual segregation and weighting of each individual waste element in the skips are performed. At the moment, the data from a single skip in this data (skip 1) is available for analysis. Table 1 presents the results obtained in the manual assessment of skip 1 waste and the comparison with the results obtained from the proposed AI system.

Skip 1 contained 1830 different waste elements at the time of its removal from the site. The total weight of the waste in skip 1 is approximately 1650 kg. The results obtained show that the current approach is incapable of correctly estimating the exact weight with over 38% error. However, the overall inaccuracy is not translated towards the waste composition. Per class, the average accuracy of the weight composition varies from over 96% to almost 99.5%.

Table 1: Comparative results of skip 1 weight composition.

Class	Real Weight [kg]	AI Weight [kg]	Real % Comp	AI % Comp	AI Error
Glass	11.9	8.8	0.7	0.9	0.15
Metal	169.12	127.0	10.3	12.6	2.30
Brick	567.2	317.8	34.4	31.4	2.97
Plastic	202.8	136.4	12.3	13.5	1.19
Wood	197.38	76.8	12.0	7.6	4.37
Insulation	481.6	336.4	29.2	33.2	4.05
Ceramic	19.8	8.7	1.2	0.9	0.34
Total	1649.8	1011.9			

This confirms that there exist inaccuracies, especially in bounding box regression, that lead to significant errors in volume and weight estimation in individual and cumulative detections. Indeed, the model given performs poorly as a weight estimator. However, that does not translate directly into an inaccurate waste composition result. In fact, it is the complete opposite. It was also noted that while some inaccuracies in classification exist in the model output, it has little to no effect on weight composition results.

The explanation is quite simple, the model error mean of variance across the dataset (if treated as a Gaussian distribution) is almost null. While error mean and variance across individual instances are non-null values, variance range allows for positive and negative values to compensate each other. In practical terms, that means that detections with an over estimated weight are compensated across the weight composition by detections with an underestimated weight.

Discussion

This system presents an alternative to manual waste audits and estimations. The proposed system enables more effective data-driven resource allocation and operational planning by providing data on waste generation and composition. The ability to monitor waste streams in real-time also allows for proactive interventions on waste management issues, such as optimising collection times, reducing overflow incidents, and identifying potential site issues that may result in the over-generation of wastes.

The automation provided shall reduce the cost of waste auditing on sites, enabling the optimisation of waste reduction policies. These policies can then expand to include circular economy and recycling. Accurate data brings evidence that supports the development of targeted waste reduction campaigns. The system's simplicity should enable it to be deployed across diverse projects, from urban households to industrial facilities, and can be adapted to local waste management regulations and practices.

Certain limitations should be considered. The system presents high initial costs, an inherent fragility against accidents with heavy equipment, and a data management infrastructure required. The collection and storage of waste data raise concerns about privacy and cybersecurity. Unauthorised access to data could lead to misuse or exploitation. The integration of multiple technologies necessitates specialised expertise for installation, maintenance, and troubleshooting. This may pose a barrier to adoption in regions with limited technical capacity.

The successful implementation and data-driven CWM approaches depend heavily on proper action taken afterward. For example, waste segregation guidelines should be established to which site workers must adhere. Cultural resistance to change and lack of awareness across subcontracted crews can hinder system effectiveness. Also, the absence of standardised protocols for waste data collection and reporting, with complex and different waste classifications depending on the waste stream, complicates the integration of continuous waste data into existing regulatory frameworks.

Nonetheless, the system proposed provides policymakers with granular data to design evidence-based waste management policies. It also enables the enforcement of waste regulations through real-time monitoring and accountability mechanisms. By improving waste sorting and recycling efficiency, this system supports the transition to a circular economy, where materials are reused, recycled, and repurposed, minimising waste generation. The transparency offered by data-driven waste management approaches can foster greater awareness of waste generation patterns across stakeholders and encourage behavioural change toward sustainable construction and waste disposal practices. Finally, the data generated can serve as a valuable resource for researchers studying construction waste composition, decomposition rates, and the environmental impact of different waste management strategies.

Conclusions

Computer vision offers significant potential for facilitating the transition from manual identification to automated detection and classification of construction waste. The amount of waste generated during new construction, demolition, and renovation projects is considerable and imposes local and global environmental challenges. The construction industry can improve its leverage and contribution to sustainability and circular economy through efficient waste management. Such efficiency can be attained by many strategies, including the structured and accurate real-time quantification of construction waste.

This proof-of-concept study aimed to demonstrate the feasibility of using vision-based systems to quantify the various types of waste generated at a typical construction site. The contributions of this research are:

1) An initial development of a system for construction waste quantification. The proposed system is built on three sequential modules (i.e., skip load/unload, waste tracking and classification, and time series of detections of each waste class). These modules are executed on each captured frame and feed into a weight estimation module that computes the percentage of waste types after a skip has been unloaded.
2) The study offers practical steps to set up the proposed system and obtain insightful information about the percentages of different waste categories found in a typical residential construction project. The proposed system enables the realisation of a practical data-driven approach that supports sustainability and circular economy in the construction industry. Interested researchers can benefit from the findings of the study and adopt similar approaches to quantify the waste generated in construction sites as a first step toward effective waste management strategies (e.g., reduction or recycling).

Future work includes tackling identified limitations of high initial cost where wider adoption tends to reduce the unit cost associated with the initial system setup. Also, associated challenges include possible accidents on sites affecting the system installation, privacy and cybersecurity concerns, and the lack of expertise to install, maintain, and troubleshoot the system. Moreover, a more comprehensive validation of all the results (i.e., for waste collected from skips 2, 3, and 4) is to be carried out as part of ongoing and future research work. The comprehensive validation is anticipated to support the preliminary results obtained in this study and enable further enhancement and optimization of the findings to draw more generalized conclusions.

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