WASTING TIME: AI, CONSTRUCTION WASTE AND THE PROBLEM OF ESTIMATION

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Abstract

This manuscript reports on the problem of construction waste, specifically difficulties with accurate estimation. The purpose is to understand why quantifying construction waste is problematic, as well as how and where it can be improved. The methodology includes an expansive literature review as well as periodic industry workshops to share data and validate interim findings and decisions. Findings reveal current techniques for waste reduction are largely confined to construction sites. The geographical and methodological diffusion of these sites makes aggregation and accurate estimation problematic. It points to landfill and transfer stations as a key point of convergence to improve observation and estimation. However, the quantity of waste at these locations makes detailed quantification difficult. An initial pilot study uses artificial intelligence to categorise and quantify large volumes of waste. While it does not prove a panacea, outcomes show promising preliminary results for automatically categorising and quantifying waste without manual intervention. The research adds to the body of knowledge by highlighting the potential of AI tools to positively impact and enhance waste estimation by incorporating more granular and automated methodological approaches.

Keywords: construction, waste, artificial intelligence, estimation

1. Introduction

It is approximated that construction waste contributes to one-third of all landfill (Behrens et al., 2007; Bossink and Brouwers, 1996; McMeel and Petrović, 2022; Purushothaman and Seadon, 2020; Schandl and Eisenmenger, 2006; Schandl et al., 2018;). Additionally, it is estimated that 30% of materials delivered to site are wasted (Osmani, 2011). There is no single reason for this although case-studies by the British Research Establishment (BRE) provide some insights (McGrath, 2001). Based on three construction site case-studies, McGrath found that off-cuts account for approximately 20% of waste, packaging accounts for approximately another 20%, damage another 20%, and poor storage accounts for 6%. With the remainder comprising a variety of miscellaneous reasons. Findings varied quite considerably across the three case studies, resulting in the research team being unable to identify any comparative patterns. This is one of the difficulties of estimating construction waste – the variety of construction sites and the difficultly in establishing stable and consistent methodologies for all cases. Additionally, waste quantification relies on manual labour intensive techniques, thus only a small percentage can be accurately sorted and quantified. From these samples data is then extrapolated to arrive at national or regional figures, however they are necessarily highly approximate. The site is not the only place where waste is estimated. Quantification also takes place at landfill sites and transfer stations. This has similar limitations to construction site case-studies, a reliance on quantifying a small percentage and extrapolating. These methods will be discussed in more detail in Section 2.

There is no question the construction sector needs to reduce its waste. As discussed there are a multitude of causes such as off-cuts, packaging damage and storage. Waste is also generated within the supply chain, which is beyond the scope of the literature reviewed. Furthermore waste creation can be a result of design decisions made prior to construction starting. Thus, waste reduction will be through a multitude of strategies that must encompass design, supply chain and construction process. However, there remains the significant problem of how to evaluate these strategies when data is reliant on such a low percentage of observation and such a high degree of approximation.

1.1. Surplus in the business model

Waste is a result of material being rendered unusable or unwanted. There is another interconnected concept built into the business of construction that is problematic. The concept of surplus, which is the practice of procuring more material than required. This practice may take several forms. Contractors allow for a surplus of material to account for expected damage, during the building process. Suppliers may prove more material than requested to strengthen or build relationships to secure future work. Furthermore contingency sums are built into almost every building contract (Levy et al., 2021). This is usually a percentage of the overall cost, and is an allowance for unforeseen events or mistakes. Although this is not explicitly surplus it a contractually included sum available to secure more services or material. In many contractual arrangements it can be used at the discretion of the contractor with no over sight (Levy et al., 2021).

The culture of oversupply, is not driven exclusively a pragmatic or logistical concerns. It is also part of human behaviour and culture, what anthropologist call the gift economy (Hyde, 1983; Mauss, 2002;). This is the phenomenon of giving in the expectation it will encourage reciprocity; in this example in the form of return business. Rather than surplus being seen as problematic it is perceived to be important in the day-to-day running of projects. In the event of something unforeseen this surplus can be moved around projects to maintain progress and ameliorating some of the perceived brittleness in the complexities of the construction process.

The cost of material waste and surplus is ultimately passed onto the clients funding the project. Consequently, there is little economic incentive for contractors to redirect and reuse. In fact, salvaging surplus and redirecting waste comes with additional logistical challenges. Some materials are bulky such as timber, and require interim storage space. Some are moisture sensitive like plasterboard and prone to degradation. Others are brittle or delicate like glass, with a high probability of damage during reclamation. Thus, it is simpler for these remaining materials to be discarded rather than reclaimed.

In summary the underlying causes of surplus and waste are a combination of normative behaviours, as well as logistical and cultural factors. They are deeply entrenched in the business-as-usual approach to construction, and consequently they are not easily disentangled and addressed.

Although there has been a steady focus on productivity—of which waste is a factor—since the 1990's. Two influential reports in the UK—the Egan and Latham reports—outlined problems and recommendations to solve some of the problems in construction (Egan, 1998; Latham, 1994). Most notably they propose a contractual innovation now recognized as Alliancing, Public Private Partnerships (PPP) or Early Contractor Involvement (ECI). These contractual innovations were intended to encourage collaborative—and thus more efficient—project. They offered an alternative to traditional contractual approaches based on punitive punishments when a party is in breach (Hinze and Tracey, 1994). However, the main limitation to this form of contract is its limited application to large projects. Which is problematic as 80% of the construction sector is comprised of small to medium sized enterprises (SMEs). As a result, improvements from this contractual approach only extend into a small percentage of projects. More recently we see the emergence of waste champions and an increase in buy-back schemes by material suppliers (Elgizawy et al., 2016). However, project and business size continue to be a determining factor in these cases, limiting their deployment to only larger scale entities.

Additionally there are software solutions to the problem of waste. Bespoke software for waste audits through categorising and quantifying waste have been tested with positive results (McGrath, 2001). Utilising BIM for waste minimisation at the design stage has also the subject of research (Liu et al., 2011; Rajendran et al.,2012). However, software solutions to waste minimisation seem to remain predominantly theoretical, with only a few making the transition to into practical operation. They appear most promising when used for auditing and where they are clearly targeted, for example reducing plastic and packaging (Berry et al., 2022; Hernandez et al., 2023, Low et al., 2020).

In summary this section has outlined the limits to observing and estimating waste. It is manual, laborious, expensive, time consuming and as such not easily scalable. Additionally, there seems to be limited technology being deployed to assist with this. It has also outlined how surplus and waste are woven into the culture of construction and difficult to systemically change. It raises an important question whether the construction site is the best place to study and reduce waste? Addressing waste further back through the supply chain has its merits. However, the aggregation of waste on site and at landfill or transfer stations make them suitable locations for obtaining accurate measurements of its composition.

2. Methodologies

Section 3 conducts an analysis of existing methodologies for quantifying the composition of landfill. This is to better understand the state of the sector and current best practice for estimating waste. The review of current waste quantification methodologies took the form of a desktop literature review. Three geographical regions—North America, Europe and Oceania—were targeted, with governmental and regional council websites being the primary corpus for accessing official and approved methodologies for handling and estimating waste. The literature review of existing research focused on the Scopus corpus. Data was sampled and collected using a keyword search, and the data was analysed using manual thematic analysis techniques. Section 4 reports on an original research project to fill gaps in quantification and composition revealed in section 3.

3. Results of review

3.1. Current waste quantification methodologies

This section reports on methodologies for estimating the composition of landfill. Approaches to measuring waste vary significantly from country to country, even within a country they may be determined—and differ—at regional levels. It proved difficult to find authoritative and comprehensive documents in both Europe and North America. This was a consequence of complexities and differences at regional levels, and broken links to key documents. Methodology documentation can be contained deep within policy documents, which—in turn—can be widely distributed across different branches of government and their websites. Additionally, construction and demolition (C&D) waste can be exempt from measurement and quantification in some regions, making the aggregation of any data gathered unreliable. Thus, even where methodologies exist, when research reports on C&D waste it is highly approximate.

Due to difficulty in finding comprehensive waste management methodologies in North America and Europe, this section will focus on Oceania, specifically New Zealand. It was chosen as the focus for a number of reasons. As an island it is a geographically isolated country which has a single waste management approach. This policy is published online, with relevant appendix linked and available. Thus, for the purposes of illustrating limitations within typical waste quantification policy New Zealand's approach is used here as an example. The Ministry for the Environment (MfE) clearly defines and publishes its methodology (New Zealand MfE, 2008). It is comprised of two distinct techniques:

- Sorting and categorizing. A small quantity of landfill waste is separated, categorized and weighed. This is then used as a basis for estimating the composition of larger quantities without additional measurement.
- Visual inspection. Categorization and composition is based on visual observation.

The table below is an excerpt from a case study and it serves to illustrate how small a percentage of waste is actually accurately measured (New Zealand MfE, 2002). Over a specific time period the total number of cars, trucks and trailers entering a municipal landfill were counted. The percentage of these inspected using one of the two methods was also calculated. The results are in Table 1. Additionally, C&D waste is singled out in the case-study as being highly problematic, with assessors failing to find 'a satisfactory, practical method for obtaining a random subsample of such a load without introducing bias' (New Zealand MfE, 2008).

Table 1. Total quantity of vehicles and percentage inspected

	Cars	***Trailers***	***Trucks***
Quantity	2939	5349	1513
Percentage quantified	0.2	0.9	2.4

The table illustrates the small percentage of landfill inspected. Furthermore, within this small percentage of waste quantified there is additional room for error. First, method one relies heavily on the sample quantified being representative. This is virtually impossible with C&D waste as its composition changes throughout construction projects. There are significant Health and Safety (H&S) challenges with manual sorting and weighting. These factors limit the extent to which this method can be scaled. The main limitation of method two is observational bias. This is the tendency of an observer to inadvertently overlook some types of waste while being highly sensitized to notice others.

This section illustrates why the quantification of landfills and waste is highly approximated. Existing methods are manual, labour intensive and restricted to a very small percentage of overall waste. They are also not scalable in any meaningful way without a dramatic increase in labour cost and an increase in H&S risk. Where waste is sorted and quantified there is inherent observational bias as well as inaccuracies if the sub-sample measured is atypical. These methods are not suited to the granular quantification required to achieve higher accuracy. Fundamentally, the construction sector needs to dramatically reduce its waste and accurate measurement—not estimation—is necessary to assess if waste reduction measures are working.

3.2. Literature review of current research improving landfill estimation

This section reports on a literature review intended to ascertain how work in the current research landscape is advancing more accurate quantification of landfill and C&D waste. This reviewed focused on the Scopus corpus using the search parameters: *landfill AND methodology AND composition AND quantification AND measuring*. Of the 608 results returned the terms *leachate* and *emissions* featured frequently. That research pertains to CO2 emissions and unwanted discharge from landfill and not concerned with composition. Consequently, the search term was amended to also include *NOT leachate NOT emissions*. This returned eighty-six results with the key themes, frequency and domain illustrated in Table 2 below.

Table 2. Summary of literature review themes and domains

Theme	***Freq***	***Domains***
Waste Management / waste	29	Waste Management / Sustainability / Resources / Smart City /Env Science
Recycling	17	Waste Management / Resources / Env Science / Food tech
Solid waste	10	Chemistry / Land development / Waste management
Food waste	9	Chemistry / Waste Management / Sustainability
Chromatography	12	Chemistry
Concentration	8	Chemistry

There are two predominant methodologies within the 608 papers, extensive reviews of existing literature and novel experiments to quantify or audit waste. The main drawback apparent within the research being context differs significantly from paper to paper, consequently no one approach appears to be generally applicable. The unique context calls for unique contextual experiments which in many cases do not find application beyond the research. Within these results twenty-six specific articles made reference to estimation, construction or methodology, of these only six (illustrated in Table 3) focused on quantifying landfill composition.

Table 3. Breakdown of subject and number of results

Subject	*No of papers*	*Reference*
Stakeholder management of C&D waste	1	Frempong-Jnr et al. (2023)
Estimation within BIM / software	2	Akinade et al. (2016) Covián et al. (2010)
On-site case-study	2	Forsythe et al. (2018) Huang et al. (2022)
Landfill analysis	1	Aurpa et al. (2022)

The remainder of the papers were focused on waste reduction through topics such as design, logistics or other novel interventions for case-study. This literature review reveals a very limited percentage of current waste research is concerned with improving the accuracy of waste quantification. Additionally four of the six papers use labour intensive case-studies, analysis or questionnaires. Which returns us to the central problem inherent within waste quantification, that existing methodologies are predominantly manual, not automated in any way and will be difficult to scale. When combined with findings from the previous section—that current methodologies are resulting in highly approximate data—it is possible to state the following:

- Absence of consistent methodologies makes national aggregation of data difficult and unreliable. Even where there are clear methodologies (such as New Zealand) the data is highly approximate.
- Monitoring the effect of waste mitigation activities at all levels (site, regional, national) will be difficult to validate without accurate data.
- Currently techniques are not scalable to acheive the accuracy required.

Any significant change in C&D waste will require a variety of interventions. This may be legislative, local council policy or implementation of performance indicators for construction companies. In all cases detailed data will be required to assess efficacy of these interventions. The review has demonstrated existing practices cannot be relied upon for more accurate estimation. This section has shown no significant current research that would result in the step change required to quantify waste more effectively.

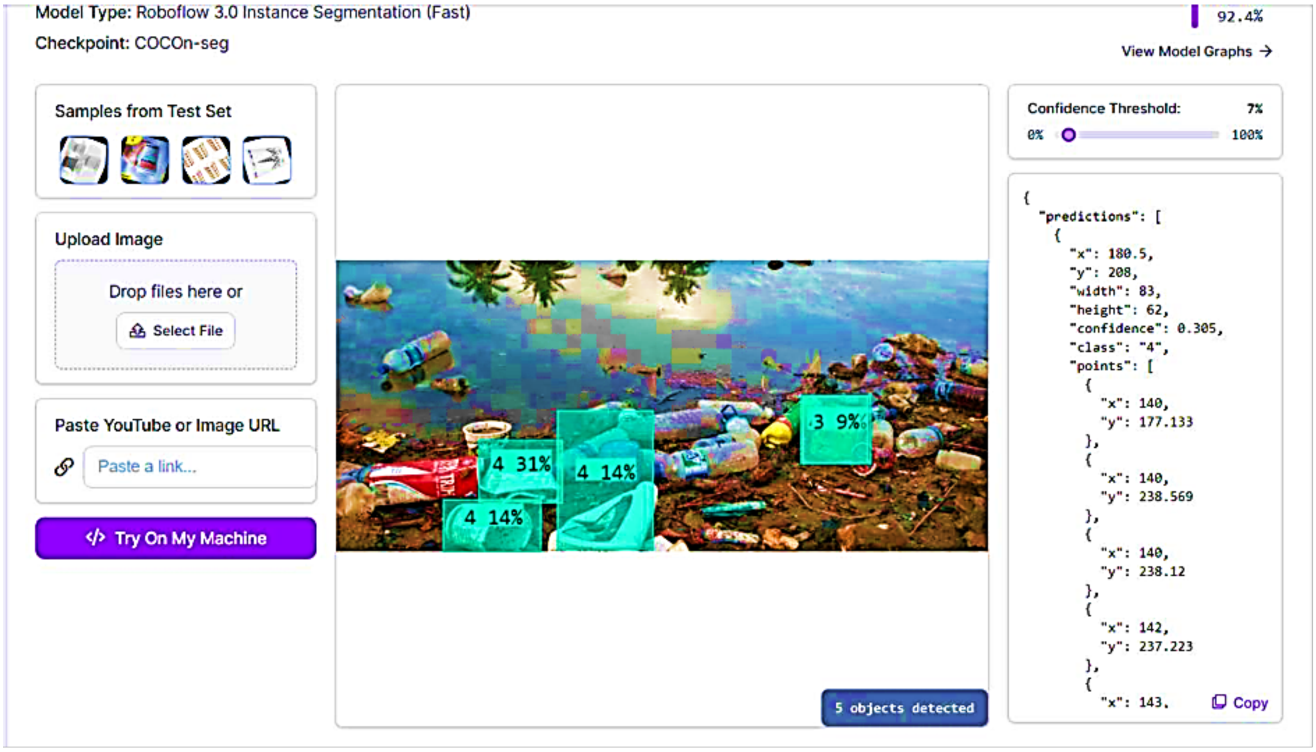
4. Original research: AI and waste quantification

This section documents our original research in developing an artificial intelligence (AI) to recognise waste. The last decade has seen significant advances in AI. Several text-based AI's—OpenAI's ChatGPT and Microsoft's Bard—have come to centre stage. They are trained on a corpus that encompasses much of the information available on the internet. They can engage in text conversation, distil information from the internet and complete reasonably sophisticated tasks. Additionally, there are AI based around imagery. DALL-E and Midjourney are most accessible and by inputting a combination of text and images these AI can generate original images. These AI systems and the models they use are becoming highly sophisticated and specialised.

Whereas existing image recognition technologies are limited to explicitly recognising and identifying features from images, AI offers additional knowledge and case-based predictive capabilities. For example, using data from previous examples to more accurately make predictions from the limited data available from a current case. Models have been trained specifically to review and summarise legal documents (Zhong et al., 2019). Essa et al. have developed a use-case using AI to identify specific flaws within a specific image (2020). Indeed, there is promising research demonstrating successful categorisation of municipal waste (Malik et al., 2022). From this preliminary investigation it appears highly likely that this research can be extended to not only categorise but also to quantify waste from images.

4.1. Training an AI model to recognise and quantify waste

A variety of freely available online AI tools were initially explored, eventually settling on the user-friendly Roboflow. A freely available data set of waste images was used for training a model specifically to recognise rubbish (Fig. 1).



Model Type: Roboflow 3.0 Instance Segmentation (Fast)
Checkpoint: COCOn-seg

Confidence Threshold: 7%

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{
  "predictions": [
    {
      "x": 180.5,
      "y": 208,
      "width": 83,
      "height": 62,
      "confidence": 0.305,
      "class": "4",
      "points": [
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          "y": 177.133
        },
        {
          "x": 140,
          "y": 238.569
        },
        {
          "x": 140,
          "y": 238.12
        },
        {
          "x": 142,
          "y": 237.223
        },
        {
          "x": 143,
```

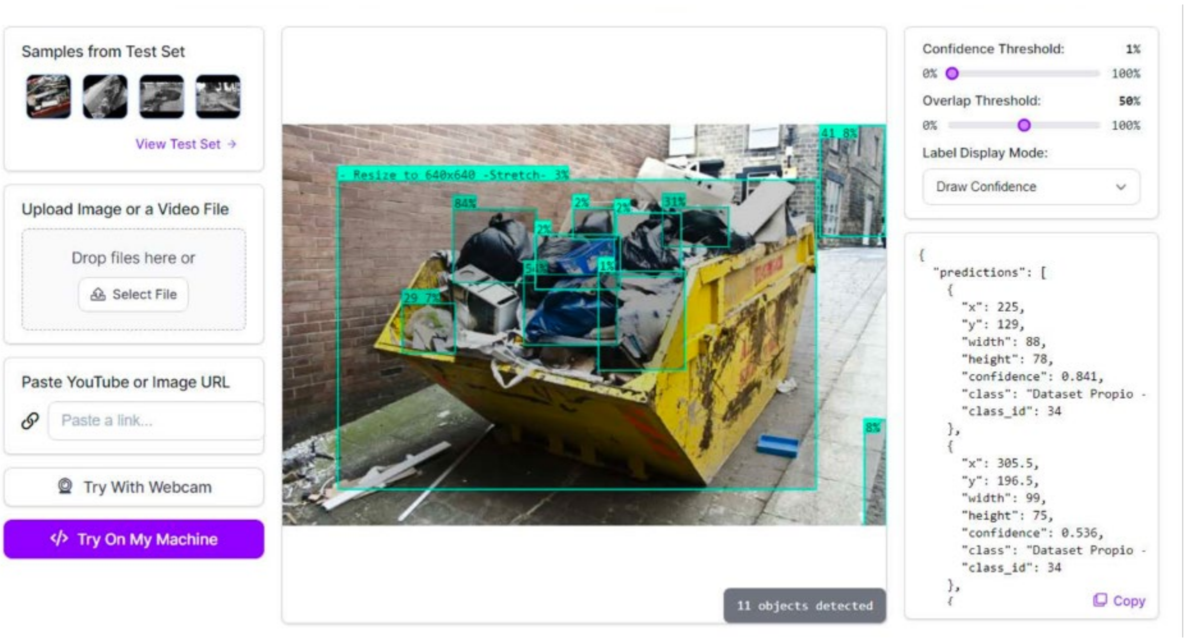
Fig. 1. Prelimiary test of recognising rubbish from an image

In an initial test of the model pre-trained with this data set the AI was able to perform three key tasks: identification, categorisation and quantification.

- Identification: Indicated by the areas highlighted by boxes in Fig. 1. This is the identification task required.
- Categorisation: The first number (3 or 4 in this case) in each box in Fig. 1 represents the machines attempt to categorise the object. The second number—a percentage—in each box represents the AI systems *confidence* in its categorisation of each object in the image.
- Quantification: On the right hand side of the image you can see it is also returning coordinates from the image creating the bounding box of the object. This can be used to calculate the overall area of the image that each type of waste accounts for. While this is highly approximate this is the third key task, it offers the possibility of quantification of the identified objects in the image.

4.2. Training an AI model to recognise and construction specific waste

The next phase was to train this AI on images that were specific to construction waste. The previous phase used generic images of waste. In the images that can be seen in Fig. 1 the items of waste are relatively spread out and clearly visible. While some are distorted out of shape, they are still readily recognisable. This phase will focus on the system’s ability to identify waste that is mixed in skips as illustrated in Fig. 2., as skips are the most common collection method on construction sites.



Confidence Threshold: 1%
0% 100%
Overlap Threshold: 50%
0% 100%
Label Display Mode: Draw Confidence

```
{
  "predictions": [
    {
      "x": 225,
      "y": 129,
      "width": 88,
      "height": 78,
      "confidence": 0.841,
      "class": "Dataset Propio -
      "class_id": 34
    },
    {
      "x": 305.5,
      "y": 196.5,
      "width": 99,
      "height": 75,
      "confidence": 0.536,
      "class": "Dataset Propio -
      "class_id": 34
    },
    {
```

Fig. 2. AI recognizing mixed waste in a skip

A similar methodology was used, a set of images was used to train the AI model with specific itemised categories of waste. Then a second set of original images of skips filled with rubbish were fed into the AI for identification. The AI then attempts to recognise those specific categories of waste in the new image. Fig. 2 is an example of the results, the AI continues to generate boxes and values attributed to those boxes indicating a numeric *category* and a percentage *confidence* weighting. While the AI was somewhat successful in this task, in the next session we will discuss the limitations and implications of this method for categorising and quantifying waste.

5. Discussions

This research has shown the complexity of trying to accurately quantify waste. Section 3 discussed domestic waste being relatively specific and consistent. Arriving at municipal landfill in plastic bags makes it relatively straightforward to unpack, categorise and weigh. It relies heavily on manual labour and extrapolating the overall quantity from a relatively small sample set. By contrast C&D waste arrives to landfill in skips or lorries. Unpacking and categorizing this type of waste at this volume is unsafe and impractical and estimation is based on visual inspection techniques. However, a very small percentage is visible and this technique suffers from observational bias. Visual inspection is recognized as being less accurate than unpacking and categorizing. Thus, any quantification using these techniques will be highly approximate. Furthermore, attempts to compare and contrast existing literature different national and regional approaches to waste estimation and quantification were problematic. As discussed the approved methodologies can be buried within a myriad of legislation and documentation. C&D waste specifically can be subject to esoteric caveats, and as a result it may be exempt to legislation or excluded from official calculations and quantifications. Consequently the ability to compare and the value of comparison was significantly diminished. However, using the relatively robust case of New Zealand we were able to outline some of the ubiqitous issues that are common within typical approaches to waste estimation.

The review of current research in section 4 suggests this will not change in the immediate future. Ongoing research into waste reduction is not specifically targeting better methods for quantification. When the literature was analysed the research was concerned with stakeholder management and software estimations (Akinade et al., 2016; Covián et al., 2010; Frempong-Jnr et al., 2023). Furthermore predominant methodologies utilised manual case-studies and analysis (Aurpa et al., 2022; Forsythe et al., 2018; Huang et al., 2022). The issues of how to automate and scale quantification and estimation do not feature in any significant quantity in the main body of literature. The review does reveal the breadth of the problem and the manifold areas which require significant research to solve this problem. Waste reduction is being tackled through design strategies, implementing novel site logistics and educating for behavioural change. However, without accurate data assessing the efficacy of these changes at a broader national level will be highly problematic.

The proof-of-concept AI system developed and discussed in section 5 was rudimentary but successful to some degree. This system continues to rely on identifying waste from images, and these images have a limited percentage of the skip visible. This also results in an unknown quantity of waste. Different methods could be adopted for capturing images, alternatively predictive AI capability could be used. Where AI differs from simple image recognition is its ability to make predictions based on previous case data. Thus based on what can be identified, the type of project and the phase of construction is can make predictions based of similar projects which have been completed and fully categorised and quantified.

Predictive AI’s are emerging and in testing finding some success in both vaccine development and cancer treatment (Bagabir et al., 2022; Thomas et al., 2022). In both these instances large accurate datasets are required. For example, an AI is trained on a dataset of successful vaccines to then shortlist potentially successful vaccine designs from a selection of possible vaccine designs. Or a dataset of cancer diagnosis, treatment and outcomes are used to assist decision-making for new cases. However, these predictive examples need to be trained on a large body of accurate data. Once again returning to the underlying problem, it appears that accurate and representative datasets will be required automate and accurately measure C&D waste. These datasets are consistently present in research from other domains (Essa et al., 2020; Malik et al., 2022; Zhong et al., 2019).

There are a number of limitations to this research. First, limited time and resources resulted in a failure to obtain comparative waste management policy from Europe and North America. This proved more difficult than anticipated, as a result the paper focused on the most readily available policy which was New Zealand. Second, a very specific and narrow keyword search was necessary for effective manual analysis of the results. A computationally assisted reviewed of a wider search terminology would likely provide additional insights. Finally, the original research project demonstrated a proof-of-concept only. It would be valuable to conduct a more empirical experiment to assess the precision of such methods on construction sites.

6. Conclusions

What goes into landfill is important, as it can result in leachate, emissions and reactions if unexpected chemicals come into contact. Current estimation methodologies are good, but highly approximate and not scalable without large increases in labour cost and health and safety risks. Additionally, at an governmental level accurate estimation is key to assessing if actions (policy, legislation, taxation or training) are working. Initial research experiments reveal computer vision systems and AI are not a panacea however, they hold the possibility of scaling and increasing data gathering. They offer the possibility of providing a detailed inventory of what is going into our landfill that is as yet completely out of reach.

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