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ON-SITE WASTE MANAGEMENT: A USE CASE OF LEAN CONSTRUCTION AND ARTIFICIAL INTELLIGENCE SYNERGY

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ABSTRACT

The construction industry generates more waste than any other industry. Waste management is getting more and more attention as the policies and mentalities evolve to face the challenges ahead: climate change, materials shortage, circular economy. Most of the waste management activities consist in waste sorting and is carried out downstream of the construction execution, resulting in lower material recovery performance. This paper proposes a method to segregate waste (separate waste based on how it is created) to enhance the reuse, recovery, and recycling of construction waste. Therefore, it investigates the applicability of Lean Construction methods and Artificial Intelligence (AI) tools and their potential synergy. Directly applying classical waste management AI tools (as used in recycling centers) was tested based on real case data. It required an excessive need for data and training. Alternatively, a Lean Construction framework based on a combination of the 5S method, and the Takt Time Planning method was proposed. It enables the streamlining of flows in order to mitigate the impact of on-site constraints on AI training. We instrumented this Lean Construction approach with an AI tool that checks the quality of the construction waste segregation process by detecting mixed materials in dumpsters.

KEYWORDS

Lean Construction, process, sustainability, Artificial Intelligence, waste segregation.

INTRODUCTION

Inspired by the Toyota Production System, Lean Construction aims at a systematic reduction of wastes within the production processes related to construction. To be applicable and relevant for the construction sector, the original list of seven wastes from Ohno was supplemented based on the Transformation Flow and Value theory of production (Bølviken, 2014). In addition to the original time losses, Lean Construction also put emphasis on material losses and value losses. Material losses, consisting of Excess Inventory and Scrap waste (Ramaswamy, 2009) have indeed been highlighted as a major problem for the construction industry (Formoso, 2002).

Reducing material wastes in construction is also a major concern outside of the Lean Construction Literature because the tremendous amount of CDW (Construction and Demolition Waste) has a tremendous environmental impact worldwide. For example, in France, CDW represents 70% of the total waste (Ademe, 2021) and 30% of total waste produced worldwide (Papargyropoulou et al., 2011). On average, more than 35% of CDW will and up in landfills annually (Menegaki and Damigos, 2018).

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As an answer, Construction waste management processes aim at identifying, reducing, reusing, and recycling materials generated during construction to minimize their negative impact on the environment and turnover (Olabode, 2019; Esin and Cosgun, 2007). However, there is a lack of data about the handling costs of waste to drive companies towards more significant effort and investments, and notably to justify the investment on dedicated technologies. Moreover, positive incentives, such as labels and good brand image, as well as negatives, such as taxes or penalties, are not compelling enough to support diversion of CDW, and a more efficient regulatory framework and public incentives are needed (Purchase et al., 2021).

Most practices and research in the C&D Waste Management research and practice are based on a "3Rs" principle, which refers to reduce, reuse, and recycle and establishes a classification of the actions related to Waste Management arranged according to their impact to the environment (Peng, 1997; Kazerooni, 2012). Further possible "Rs" have been proposed, but an overarching principle remains to prevent as much disposal as possible: waste that cannot be reused or recycled, will most likely end up being burnt or landfilled (Nagapan, 2012). All material waste that cannot be reduced should be kept reusable or recyclable, which requires separating the various types of materials. Considering the climate emergency, recent regulations put a growing emphasis on these principles while becoming more compulsory. For instance, the revised waste management law in Luxembourg compels construction companies to sort 7 types of materials during the execution phase: wood, inert materials, metal, glass, cardboard, plastic, plaster, and hazardous wastes (Ministère de l'environnement, 2022).

For a construction company, such new regulation implies extra cost for sorting scraps in the mixed waste dumpster or being able to handle separate flows for material wastes. In both cases, the added costs or activities fit within the Lean taxonomy of waste (Bølviken, 2014) and should thus be considered from a Lean Construction perspective.

Therefore, Lean Construction might answer some of the barriers to on-site sorting strategies highlighted by Bao et al. (2019). However, the Bao study also points out a lack of technological solutions. In other sectors, such municipal waste management, sorting is performed by technologies based on Artificial Intelligence (Lu and Chen 2022). The use of such technologies in construction is a topic of growing interest, as it relates to their applicability for material waste management in construction.

More recently, the interplay between Lean Construction and AI have been studied from a theoretical perspective by (Cisterna et al., 2022). The authors highlight the potential for synergies between LC and AI: material waste management might be one of these.

This article will investigate the applicability and synergies of Lean Construction and AI for the purpose of reducing disposal on construction sites.

BACKGROUND

Assisting waste management through AI is uncommon in the construction industry, even as the use of intelligent computer-vision seems very promising for object sorting tasks. Early ideas date back to 2000 (Mattone et al., 2000). Most of the waste management solutions appear downstream of the execution phase, with recycling robots (Lukka, et al., 2014) and especially in recycling centres. A lot of facilities are equipped with conveyors and robotic arms to sort waste though in some cases the sorting is operated by humans. A challenge for waste sorting derives from the fact that many wastes are already mixed, and some are difficult or impossible to separate (for example, coating with plastic and metal); this type of waste will most likely end up being burnt or serve as landfilling.

A different approach lies in the segregation, where waste is separated into dedicated containers as it is created at the workstation; this eliminates the need for later sorting activities. This approach is common in sectors like municipal waste or household waste (Lu et al., 2022) where AI-based waste segregation is performed in closed dumpsters with image recognition algorithms and automated segregation. This reduces human intervention and error by leveraging a tool able to complete segregation. However, use of such tools is made possible by the relative homogeneity and small size of the waste; moreover, these tools can usually manage only 3 types of waste (paper, plastic, metal) and are not suited for bulky and dense material. Thus, the direct applicability of such technologies is very limited in the construction sector.

Recent work (Lu et al., 2022) demonstrated the identification of precise waste elements (i.e., known as semantic segmentation) to help with the segregation and precise identification of mixed wastes. This technique may be suitable in a construction site's context though the specific training of the AI model should be adapted for a construction site's needs and operational contexts. Indeed, semantic segmentation is quite a complex AI model that requires a lot of training and that may be less robust in construction because of the variety of situations on site.

Moreover, if that kind of approach seems efficient from a technical perspective in a specific evaluation case, the role of the humans involved is not sufficiently considered, which may be particularly inadequate to construction as highlighted by Noueihed and Hamzeh (2022). Therefore, a practical waste management process, encompassing the whole waste management is needed to ensure its applicability in construction.

Regarding Lean Construction approaches, the 5S method has already demonstrated its capacity to reduce material wastes and losses of control on material flows by maintaining clean and tidy workspaces (Berroir et al., 2015), and seems thus, applicable for waste segregation. However, authors also showed that 5S should not be applied dogmatically and in isolation but combined with flow identification and management methods to streamline flows, facilitate change management, and make improvements last from project to project. Hence, a waste segregation process based on several Lean Construction tools should be proposed.

This article assumes that waste segregation should be preferred to downstream sorting. The current AI methods listed above are not encompassed in any Lean process, and thus, they may be difficult to apply in the context of CDW segregation on site. This paper will focus on enabling CDW segregation based on intertwined Lean Construction and AI.

METHODOLOGY

To investigate the applicability of AI for waste management in the specific context of construction sites, we propose to follow a Design Science Approach (DSA). The grounding of our proposition is based on the aforementioned background work on AI and Lean Construction and their related limitations. The DSA proposed artifact is a Lean Construction process encompassing an AI tool for waste segregation and it will be compared to an approach based on AI only (similar to what is applied in other sectors). The solutions will be evaluated according to the amount of data needed as well as the feasibility of the training, maintenance, and update of the AI model. Accordingly, the research was split in 2 cases:

Case n°1: AI tool without Lean

This case is based on current practices of AI implementation and training in other sectors. Research protocol consisted of:

6. Data collection from 2 construction sites in Luxembourg
7. Training of the algorithm
8. Evaluation of the amount of data and training time for an implementation on site.

Case n°2: AI tool integrated in a Lean Construction process

Considering that AI alone is not a "silver-bullet" solution to solve on-site waste segregation, this case investigates what Lean process could be applied and how it can integrate with the development and implementation of an AI solution for onsite waste segregation. The authors sought to address two questions:

How can LC enable the integration of technology in the segregation process? (Q1)

How to train and maintain an efficient AI model for on-site waste segregation? (Q2)

Subsequently, the research was conducted as follows:

9. Proposition of Lean Construction process for waste segregation on site with computer vision (using planning data from the second pilot site cited in case 1)
10. Development of a computer-vision AI model (visual waste recognition).
11. Test of first round training in controlled conditions
12. Evaluation of the amount of data and training time for an implementation on site.

A third case, "Lean process without AI," is not considered here because literature already established that such a solution would be applicable. This case needs to be studied in future research from a performance and efficacy perspective.

RESULTS

CASE N°1- AI TOOL WITHOUT LEAN

The first case was performed through the data collection of waste on two construction sites in Luxembourg. Cameras were installed near waste collection zones, above dumpsters and enabled to take one (1) photo every minute, collecting more than 25000 pictures overall. From an AI perspective, the training environment was uncontrolled (dust in the air or on the material , water, snow, overlapping materials).

These dumpsters were supposed to collect only one type of waste. However, a lot of wastes were mixed (plastic with wood, metal with plastic, plastic bags with various waste inside). Training an algorithm to identify various type of waste in such a context resulted in a time-consuming labelling phase. Half of the data was totally unsuitable for exploitation because scrap was too mixed or hidden inside plastic bags (see fig.1). In the other half of the photos, materials were altered (e.g., wood was contaminated with paint or oil) as well as overlapping materials created errors in the AI training, as did variable conditions (lighting modification, rain, snow).

Figure 1: Example of dumpster pictures used to train the model

As a result, the training time was over 200 hours, and the recognition rate was below 60%. Accordingly, implementing such an AI tool on a construction site would require training and updating the model several times during the project, as the material flows evolve. Hence this method is not robust nor suitable for replication.

CASE N°2 AI TOOL INTEGRATED IN A LEAN CONSTRUCTION PROCESS

How can LC enable the integration of AI in the segregation process? (Q1)

Dealing with messy and overcrowded workspaces is the goal of the 5S method (e.g., Berroir et al., 2015). Aligned with 5S, segregation requires to identify materials flows exiting the workspace and to be able to keep them separate as much as possible. A limitation reported during the data collection on site was the use of many plastic bags and the mixes of scraps. It was reported from the pilot projects that most of these materials were already mixed at the workspace. Small piles of materials left at the workspace rapidly tended to become mixed chunks of wastes. Separating such waste from AI automatically is nearly impossible, and the resulting waste are costly as they end up in disposal. Moreover, companies on site usually rejected the responsibility to clean up for each other, meaning that un-segregated piles of waste were challenging to process, as no one contractor had responsibility for clean-up and segregation. Hence, applying a 5S method would contribute to waste segregation as reported by Leino (2014). Main expected benefits are reported in table 1.

Table 1: Expected contribution of 5S to waste segregation on site

1st S, Sort	Systematic elimination of unused material before they get mixed
2nd S, Set in order	One place for each material
3rd S, Shine	Visual workspace: systematic cleaning, any leftover pile is visible as an anomaly
4th S Standardize	Adapted equipment (bins and container) and rules at company level
5th S, Sustain	Rigorous application of standards and inspections

Accordingly, the implementation of 5S appears highly beneficial for waste segregation, but as shown by Berroir et al. (2015), its implementation and maintenance over time greatly benefits from other Lean Construction methods. Methods that enable balancing and identifying the flows of material would enable identifying and adequately sizing the equipment required to collect and carry the waste. Such an approach was proposed by Heinonen and Seppänen (2016), learning from examples from cruise ship cabin refurbishment, they suggested improving takt time application in construction by explicitly considering logistics and garbage collection at the planning level. In practice, they proposed to implement garbage collection points but practical implementation in construction and location of the collection point was left for future study. Consequently, based on the case of the second pilot projects involved in this research, we considered several setups for such collection points.

A single "one-fits-all" setup of waste collection point would need to be suitable for segregating all types of waste generated from every task performed in the work zone. Enabling this type of collection point would require a lot of equipment since one collection point would be needed at every floor where there is some work and since the collection point should be composed of all the different containers. This option might often not be applicable for space reason, it might strongly increase costs. The opposite approach would be to define individual containers for each team with the appropriate equipment for their various waste streams. This approach might also require excessive amount of equipment since many waste streams are common to several trade and could be mutualized. Additionally, it would require workers to move all the equipment with them, which should be avoided from a Lean Construction perspective as it appears as a new time loss for the workers and is particularly not suitable in cases where they may have work in progress on several zones at the same time. Moreover, the collection of the waste by a logistic operator would require additional capacity. Lastly, this setup does not really take advantage from balancing and identifying flows of material in the way that Heinonen and Seppänen (2016) documented and would in practice look very similar to a case where everyone is managing its own wastes. Consequently, the proposed solution for this case n° 2, is to take advantage of a "takt timed" planning to find a balance between these 2 setups and to define collection point based on takt phases as for example in figure 2.

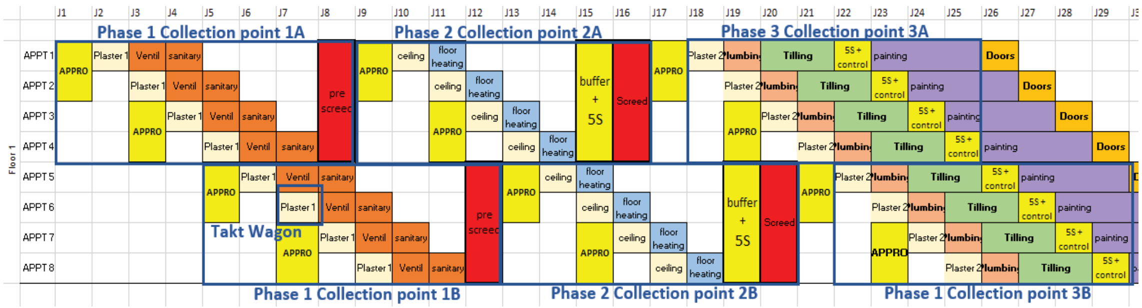

Figure 2: Example of takt timed planning extract with visualisation of the collection points

More precision on the tasks can be found on table 2, but the details of this planning is of little importance since this example only aims at illustrating the idea of defining and sizing Collection Points based on takt phases. Typical level of details of a takt times planning enables explicit consideration of deliveries and cleaning (highlighted in yellow in fig. 2). This example presents a group of tasks in different takt zones circled in blue and referred to as "phases". Implementing waste collection points at a "phase level" would result in 3 different setups of collection points, each one following a group of trades.

In this scenario, a phase encompasses half the apartments of a floor, meaning that each collection point would have 2 instances (e.g., Phase 1 "A" and "B") intended for the same flows. Thus, workers would always have access to the right container at the floor where they are supposed to work. This level of detail allows to anticipate the kind of waste managed at each collection point as illustrated in table 2. This list is not exhaustive but intended to show that material waste flows can be identified individually at the level of each collection point based during planning. Furthermore, the application of the takt time method would result in more stable amount of waste generated, thus allowing construction managers to select waste containers with the required shape and capacity.

Table 2: Identification of potential waste types at each Collection Point

Collection point	Tasks	Type of waste
CP1	Plaster (1st layer) Ventilation Sanitary Pre-screed	Plaster, Aluminium (rail), packaging plastic, pallets, Gravel, wood, tubes, cardboard
CP2	Ceiling Floor heating screed	Plaster, Aluminium (rail), plastic packaging, polystyrene, plastic tubes, pallets, Cardboard
CP3	Plaster (2nd layer) Plumbing Tilling	Tilling, Plaster, Aluminium (rail) Pallet, cardboard,
Out of CP (collected directly by subcontractor for each task)	Painting Doors Electrical	Paint can, plastic packaging, electric wire, gravel,

To ensure waste collection at each task/takt wagon level, teams should be equipped with small individual containers (e.g., big bags or rolling dumpsters) as presented in step 1 of figure 3. Material can be then brought to the collection point where containers can be equipped with cameras and a visual recognition tool trained for the relevant containers and types of wastes, as represented in figure. 3.

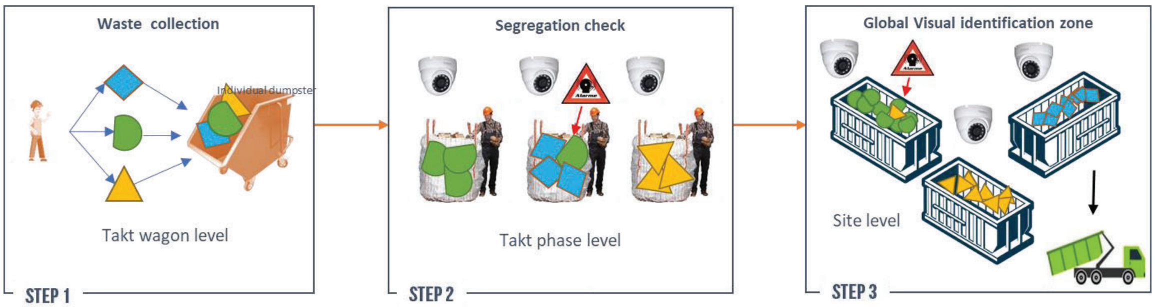

Figure 3: AI supported waste segregation process

Compared to what was performed in case 1, the waste collection points operate at an intermediary level in the management of waste flows; the control device prevents mixing of wastes, supporting "clean containers" (one type of material per container) onsite. A last control, Step 3 of Figure 3, is based on larger dumpster observation by camera. This uses a similar AI approach with different training data as the large dumpster situation is different from the small "local" dumpster situation. The large dumpster can also be a last quality control point for downstream waste recovery (even if it goes beyond our approach) to prevent costly mixed waste from leaving the jobsite. Contrary to classical "waste recovery" activities performed downstream of the execution phase, the LC framework proposed allows project teams to streamline material flows, perform waste segregation on site, and reduce the impacts of environmental constraints that hindered the applicability of visual recognition on the construction sites.

How to train and maintain an efficient AI model for on-site waste segregation? (Q2)

The key to the success of this solution is the visual recognition system that can detect and characterize each material despite the constraints of an uncontrolled environment (the construction site): dust (in the air or on the material), water, snow, or contaminated materials (painting or oil covering a part of the material). Another key constraint will be the overlapping of materials when the dumpsters will be emptied into larger dumpsters or big bags. In many cases, the materials can be partially or fully hidden from the camera.

The solution is based upon in-situ data (photos) that rely on the trained AI models introduced in the previous section. This AI, notably its training and maintenance, comes with a cost that downstream waste recovery will not face. However, it directly puts the responsibility to the person producing the waste whilst facilitating their success is the sorting of their waste (by directly providing adapted containers and explicit zones). A simple set-up was selected for the waste recognition and segregation AI model. To do so, a camera was set on top of a big bag/dumpster deployed on site. This camera helps to capture waste drop activities as soon as they occur. Indeed, the wastes are supposed to be dropped in the correct container (big-bag or dumpster). As shown in Figure 4, the technical process is articulated as follows: 1) the camera detects an activity. This step is required to avoid having a continuous execution of the waste recognition model; indeed, the model should only run when waste needs to be detected in order to reduce the energy demand from the AI system that is likely running off of batteries. 2) In a second step, the model is executed on an embedded device (e.g., a Jetson Nano card). It tries to detect the waste being dropped and whether or not this material is correct for the container (e.g., putting only wood in the wood dumpster). 3) In a third step, the algorithm warns the personnel about the correctness of waste segregation or alerts if a mix is detected, and it creates a log that keep a trace of the current detection. This trace can be used later to know if there is still mixed waste in the container, to know where it is, or to identify false positive cases that can be used for future training of the AI model.

A simpler AI approach than the one described in (Lu and al., 2022) was selected, since it's important to have: 1) a human in the loop, and 2) more robustness for recognition and thus less training. As a result, the training relies on multiple simple classification models. Each of them identifies the presence of a single material in the image captured by the camera. If more materials are recognized, then a mix is detected.

An important step of any deep-learning model is the training, mostly based on the extension of a pre-existing recognition model. Indeed, most of the recent approaches extend (i.e., use transfer learning) an already trained model based on daily-life objects (e.g., boats, cars, bananas, ducks, etc.). Basing the training on pre-trained algorithms drastically reduces the number of required photos.

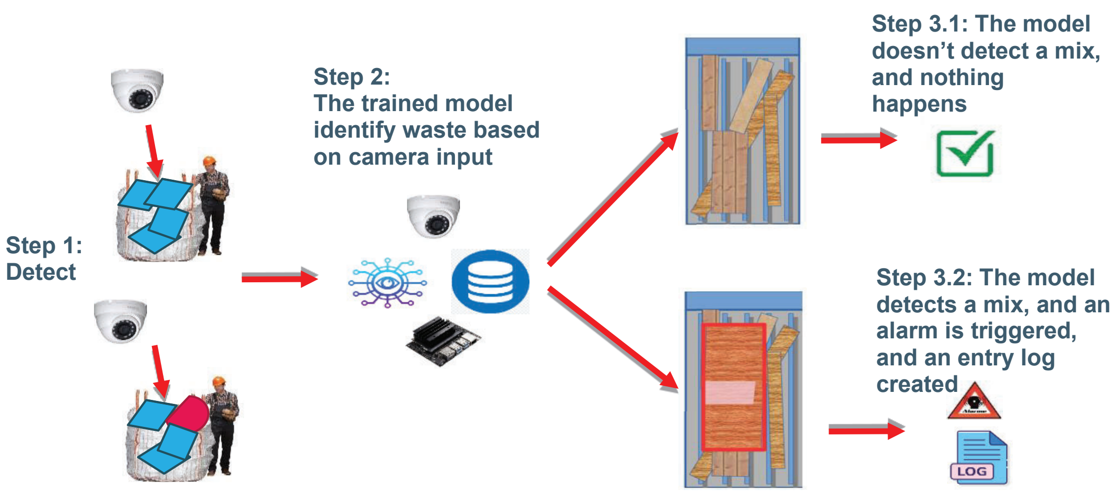

Figure 4: The waste identification technical process

Moreover, following the same principle, the training of the models has been started in a controlled environment (laboratory training; see Figure 5), with 4 basic materials: wood, metal, plaster, and bricks. It consists of around 550 images of the basic material and 550 images of the basic materials mixed with others. The concept of the first round of training was to have an already sturdy model before deploying it on-site but also diminish the quantity of data needed to train the algorithm. Certainly, training the algorithm directly with on-site data would require at least 10 times as many photos, as discussed in other studies (Lu and al., 2022), and it is very likely to face a lot of peculiar cases, thus disturbing the learning phase. Starting the training in a controlled environment allowed good recognition results (above 90%) of the 4 basic materials with fewer data.

Figure 5: Lab training sample: two upper photos brick not mixed; the two lower brick mixed

Once the results are confirmed in the laboratory, a second round of training will start on-site, with constraints (lightning modifications, dust, rain, overlapping materials, contaminated materials) to strengthen the algorithm and have a fully functional tool. This training phase will be longer since it is expected to have more mistake occurrences due to the on-site constraints weakening the algorithm's performance.

Since such AI model cannot be 100% effective, we will have to introduce 2 "bypass" buttons. The idea of those buttons is to make the system robust according to the site or construction company specifically without blocking or keeping mistakes in the automated part of the segregation process. As illustrated in Figure 6, the two buttons will help with the identification of the false positive and the false negative solution (i.e., mixed, or not mixed wastes). These bypass buttons, called "force push," will be used in case the models make a mistake. For example, the model detects a mix but there is no mix, the "Force NO MIX" button will be pressed to notify that the model made a mistake, and, hence, will learn from the mistake.

In the other case, a mix is not detected by the model, the "Force MIX" button will be pressed to notify an error, and the model will hence learn from that mistake.

If a mistake is recuring, the training will be extended through the identified wrong situation to make the system more robust. More experiments will be needed to implement a correct pace of training when there is sufficient data to make another training.

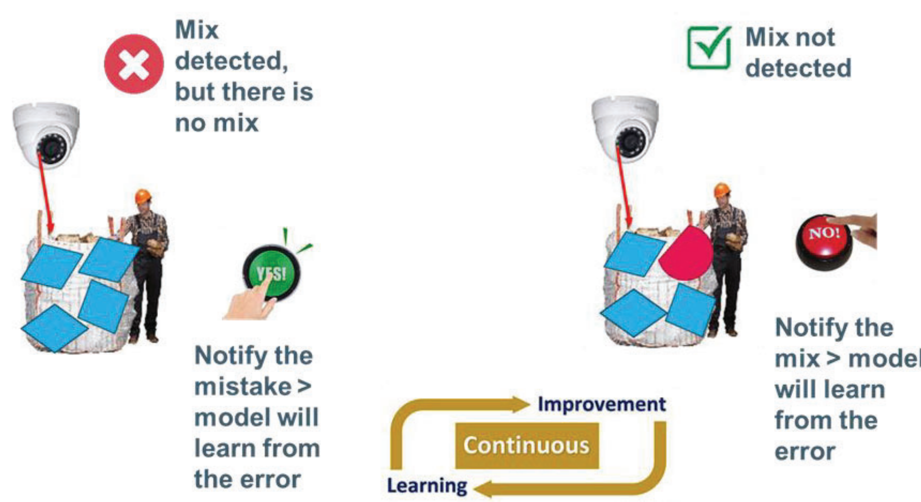

Figure 6: Notification buttons on site of false-positive and false-negative with continuous learning

As a summary, a set of simple trained models is operating, and it detects the presence or absence of each individual material on a camera. It is based on in-lab training that is enhanced with on-site image training. The results of those models are then crossed together to state if there is a mix or not. It is also vital to allow for tracking and reporting incorrect classification to enable the model to learn from the site or construction company. The idea is to be able to learn from errors to ensure a more robust detection.

DISCUSSION

The Lean Construction framework proposed in this article might be applied without the AI control tool, but with a human supervision. Further research could thus compare the Lean Construction + AI framework proposed here to a Lean Construction without AI solution according to their respective performances in real case conditions. Showing the benefits of the AI integrated solution would prove the synergy between Lean and AI for the use case of waste management on construction sites.

The explicit identification of deliveries and garbage collection in the Takt Time Planning, as illustrated in this paper, can contribute to further reductions of environmental and economic impacts of the construction sector based on the application of Lean Construction techniques. Hence, it would contribute to merging upstream (logistics) and downstream material flows (garbage collection) similarly to what is presented by Heinonen and Seppänen (2016) in the context of ship cabin refurbishment. The implementation of garbage collection would allow a third-party logistics operator performing Just-In-Time deliveries to easily collect the scraps and return them with their current (standard) vehicle, achieving an integrated reverse logistics chain and reducing the impact of transport. Further development of the AI tool may also integrate quantity estimation and forecasting to better identify when collection points should be taken off, and in what priority. This may also contribute to collecting more data about the waste generated on construction sites to provide policy makers with quantitative data from construction sites that supports defining and implementing new environmental policies.

CONCLUSION

This paper introduced an instrumented AI based process dedicated to waste segregation on construction sites. To do so, a first experiment was conducted to train an AI model without a Lean approach; it resulted in a time-consuming training and showed insufficient performance. Indeed, this first experimentation forced us to face all the on-site constraints at once, resulting in: (1) a time-consuming labelling phase for AI training (requiring a lot of data) and (2) a more complex AI approach (semantic segmentation).

The complexity of the problem can be lowered by identifying and streamlining material flows using Takt Time planning and 5S, offering a proper framework for the waste segmentation process that mitigates the on-site constraints. A simpler or more reliable AI model can thus be used, with shorter training time and less required input data.

However, the AI tool presented here is not fully functional since it has not been trained nor tested yet on a construction site, so it has yet to confront the “noise” of the environment (lightning modifications, dust, rain, overlapping materials, contaminated materials). This second round of AI training will be the core of the future work to be carried out on the tool as well as its integration on various construction site typologies.

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