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How to valorize construction and demolition wastes? Beyond the state of the art through vision systems and Artificial Intelligence tools

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***Abstract*—The efficient tracking of Construction and Demolition Wastes (CDWs) is pivotal in a perspective of sustainability and circularity in the construction sector. Sensing and digital technologies can undoubtedly play a relevant role in this context. This paper proposes an innovative approach for detection, quantification, and characterization of CDWs in order to provide information exploitable through optimized valorization routes made available via dedicated service platforms. The preliminary results are promising, and the solution will be iteratively refined and improved thanks to continuous data collection from real-world scenarios.**

Keywords—CDWs, sensors, vision systems, AI, sustainability, building life cycle, waste valorization, circular economy.

I. INTRODUCTION

In a perspective of sustainable and circular economy, it is essential to enhance the durability of construction materials and promote their valorisation and reuse at the end of a building life cycle. In this context, construction and demolition wastes (CDWs) sourcing plays a pivotal role; in fact, CDWs represent a third of the total wastes amount generated in Europe [1]. Digital technologies can help to automate detection, quantification, and characterization processes, providing information potentially useful for valorising these wastes and prevent them from being disposed, with a perspective of sustainability and circularity in the construction sector [2]. Data quality surely determines the reliability of results and sensing technologies as well as Artificial Intelligence (AI) algorithms must be properly selected to maximize the performance of such solutions. Also, the plethora of interfering factors present in real scenarios must be considered since they directly impact on the effective applicability of these tools, determining the measurement accuracy of the output.

Looking at the literature, it is immediately clear that computer vision (CV) represents a powerful tool for waste sorting, involving image preprocessing, feature extraction, and Machine Learning (ML) [3–5]. Indeed, RGB-D (i.e., sensors working in the red, green, and blue colour space, with the addition of depth sensor), Infrared (IR), and video sensors can be used together with AI technologies [6,7] and the information for CDWs classification can be obtained also in the HSV (Hue Saturation Value) colour space [8]. However, most studies consider controlled conditions to develop these solutions, namely homogeneous (black) background, conveyor belts with objects separated each other [9,10], optimal lighting, etc. Digital cameras seem to represent a major trend for future development [3]. Li et al. [6] have exploited a fusion of three-channel RGB image and single-channel depth image, trying to mitigate issues related to material heterogeneity and surface contamination. Some studies limit to determine the presence of the object of interest, others look for object detection, which also locates the object in the scene with bounding boxes [11] or even pixel areas segmentation [12].

Deep Learning (DL) based approach plays a pivotal role in the context of end-to-end Computer Vision (CV) for CDW classification. State-of-the-art Convolutional Neural Networks (CNNs) algorithms, such as AlexNet [13] and ResNet, are widely used, reporting accuracies above 96% and 85%, respectively [3]. Among other examples it is worth mentioning the YOLACT algorithm [14] and VGG-16 [15]. Transfer learning can be exploited to adapt previously trained models to a new domain [16], hence using pre-trained weights

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of models trained on a different dataset (e.g., Tensorflow [17] and Detectron [18]). CNNs have been applied to extract features, then classification is performed with ML techniques (e.g., SVM or kNN, useful when new categories are added [3]). Both single- (e.g., SSD and YOLO) and two-stage (e.g., Faster-CNN and Mask R-CNN) detector architectures have been employed together with CNN-based feature extractors (e.g., ResNet, MobileNetV2, efficientDet), but Faster-RCNN models remain the most robust [19]. Zhang et al. [20] proposed a two-stage algorithm that at first recognizes wastes into 13 classes, then classifies into 4 categories, namely recyclable waste, household food waste, hazardous waste, and residual waste. Data augmentation techniques are applied comprising scaling, rotation, shear mapping, and flipping operations. Besides noise addition (influencing the image resolution and size), blur effect (correlated with the image focus), hue and saturation variations can be considered [21].

Data annotation is pivotal; Lu et al. [22] developed a segmentation model exploiting a CV semantic segmentation technique (with a better granularity – classification is performed in a pixelwise manner [23], hence spatial geometry is more precise and better solutions for characterization and robotic sorting are enabled), namely DeepLabv3+; their trained models are available on GitHub to be further fine-tuned for specific applications.

CDW data annotation plays a critical role in the development of CV models. The wide availability of CDW datasets enables DL models implementation since these require an extensive amount of contextual information during the training stage and evaluation [16]. This poses multiple challenges due to the manual nature of the data annotation process, quality and uniformity of annotations, scalability constraints reliant of annotator expertise, annotator's bias which may lead to model bias, and technological considerations within, but not limited to, available annotation tools and infrastructure [24].

The state-of-the-art solutions (including automated sorting technologies and advanced analytical techniques like spectroscopy and chromatography) can be considered quite effective in laboratory conditions. Spectroscopy and chromatography sorting solutions are promising if combined with Internet of Things enabled technologies, in fact the score obtained linking supervised AI techniques and RGB-images and/or spectral imaging goes from 63.9% to 98.8% [25].

However, most of these techniques are not applicable in real scenarios due to material heterogeneity and heavy presence of dust. In fact, currently most of the waste management sites rely on manual classification and sorting approaches. This is obviously affected by subjectivity as well as health and safety issues, inconsistency, and cost inefficiency [26]. Advances in AI, robotics, and data analytics may further contribute to improvements in waste management processes, allowing for more accurate sorting and recycling of materials [27].

Hence, a not-negligible list of drawbacks can be identified in current technologies:

- Most of the studies are performed in laboratory conditions (e.g., simplified background, such as black conveyor belt [9,28,29], optimal lighting conditions, etc.);
- Datasets are artificially collected in non-real scenarios; also, images from the web are used for training [30]. For CDWs not many public wide datasets are available (mainly referred to residential and municipal wastes). TrashNet [31] is the most widely used, but it includes pictures of individual wastes with a white poster board as background, hence not capturing the complexity of real scenarios; however, accuracy beyond 90% has been achieved [32,33]. Lu et al. [22] built a real-life scenarios database based on images collected with cameras installed at upper-rear direction of trucks, considering both daytime and night; the annotation was performed by professional annotators via the Taobao platform. They evidenced the limits in depicting materials edges and boundaries as well as in balancing the datasets among the different classes to be distinguished.

The literature approaches cannot be applied in-field since AI models need to be trained in conditions very close to the operating ones. In real scenarios presence of dust and intricate cluttered backgrounds significantly degrade the classification models performance, as well as changing lighting conditions. In addition, CDWs are usually overlapped with each other. For these reasons, the exploitation of computer vision is still limited for CDWs sorting [3] leading to substantial opportunities for further research. Sensor combination can be a way forward (e.g., Near-Infrared Radiation – NIR – and Raman spectroscopy, spectroscopic and visual sensors, computer vision and NIR, etc. [34]); for example, thermal characteristics of CDWs can be considered using thermal sensors and active thermography [35].

Hence, the aim of this paper is to propose a methodology based on sensors and AI algorithms for identifying, quantifying, and characterizing CDWs and provide relevant information to a platform dedicated to valorisation of such materials, with a view of circularity and sustainability of the construction sector.

II. Proposed sensor- and AI-based solution

Within the framework of the RECONSTRUCT project (A Territorial Construction System for a Circular Low-Carbon Built Environment, GA no. 101082265), the Authors are developing a solution for CDWs sourcing based on sensing technologies and AI-based algorithms for detection, quantification, and characterization of CDWs. The idea is based on the collection of data with vision systems in real-life scenarios in different working conditions (e.g., lighting, presence of dust, etc.) to include the normal variability in the methodology and be robust in field applications. The proposed solution aims at being applicable to real world scenarios, hence it is trickier to be developed with respect to laboratory conditions but can be really beneficial for CDWs management. HSI (Hyperspectral Imaging) systems could be exploited to consider the spectral signature for the assessment of quality of the wastes to be valorised (e.g., Serranti et al. [36] exploited the NIR range of 1000-1700 nm).

The first step of the approach (Fig. 1) consists in evaluating different types of sensors in diverse spectral ranges, including RGB, depth, IR, and HSI solutions. Indeed, complementary information can be obtained exploiting them and this can be useful to discriminate among different classes of waste. In fact, using different input data the extraction of the characteristic features of each waste class is wider. Dimension, colour, texture, geometry, shapes are discriminating attributes for different types of waste. The collected information is hence used to build a dataset for the

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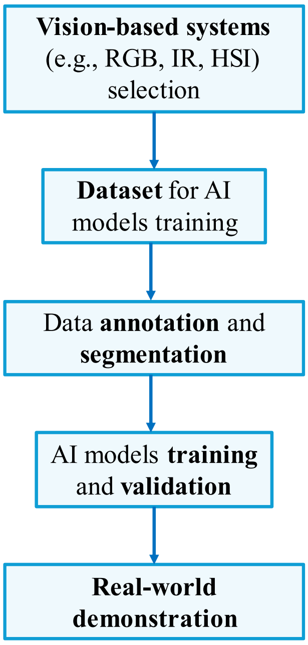

Fig. 1 Pipeline of the proposed approach.

AI model training. Accurate data annotation and segmentation of CDW samples are fundamental steps to train robust models to be applied in real scenarios. An empirical validation of the produced model efficacy is required to ensure that performance aligns with expectations under a diverse set of conditions. This enhances the stakeholder's confidence and provides a clear set of representations that highlight areas for continuous refinement. Outlining equitable biases, opening the opportunity to refine responses to edge cases and optimise model based on real world data, enable to assess the possibility of sustainable scalability. Furthermore, real world demonstration highlights the potential of AI-based tools to optimise and enhance operational efficiencies while enabling interdisciplinary innovations. It is worthy to underline that AI models trained on real scenarios can be more robust and outperform the state of the art given that they learn from real-world variety, hence becoming capable to efficiently generalize and manage new scenarios. This can be beneficial for waste management, supporting everyday activities of operators dealing with waste sorting; it is important to use the European Waste Codes (EWC) [37] to label data for the sake of interoperability, scalability, and, hence, to broaden the proposed methodology.

A. Sensors and scenarios of interest

Selecting the optimal sensors for the target application is fundamental; for sure, different constraints must be considered, such as budget, operating conditions (e.g., lighting and environmental conditions), and requirements (e.g., power supply and Internet connection for remote access to the measured data). The idea is to develop solutions scalable in terms of accuracy and complexity, depending on the requirements in terms of data quality and information of interest to be inferred from data analysis.

Diverse types of vision systems can be included in the monitoring systems, such as RGB cameras, IR thermal cameras, LiDAR sensors, RGB-D cameras, and HSI systems. Not all of them are intended to be permanently installed, some (e.g., IR and HSI systems) can be dedicated to more in-depth analyses and other (e.g., drone equipped with multispectral

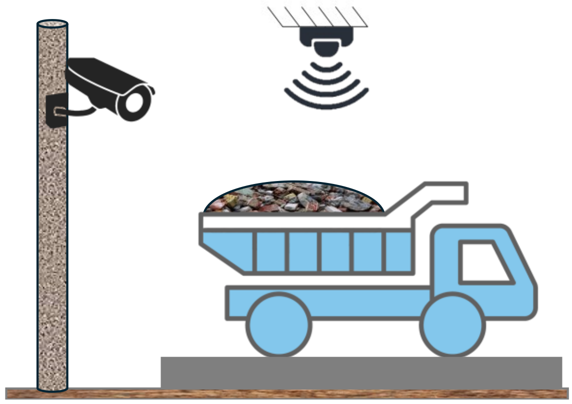

Fig. 2 Proposed experimental setup (truck scenario).

cameras) only for complementary/additional inspection operations on the site of interest. Three segments of monitoring systems could be considered:

- Basic solution, including only CCTV sensors. Both quantification and characterization of CDWs would rely on the analysis of data in the visible range;
- Intermediate solution, enclosing CCTV and LiDAR sensors (or depth sensors) to have depth data useful for quantification purposes;
- Advanced solution, incorporating CCTV, LiDAR, and IR sensors. Additional data in the infrared range can provide information useful to discriminate among subclasses of wastes (e.g., distinct types of metals).

Moreover, advanced systems, such as hyperspectral cameras and drones embedding multispectral vision systems, can supplement the monitoring system as laboratory equipment to perform more in-depth analysis on material samples of interest (e.g., discrimination among different classes of metal waste through HSI [38]).

Different scenarios can be of interest for CDWs recognition, for example focusing on trucks entering a construction/demolition/waste management site (Fig. 2), waste piles in a waste management site, and waste containers in construction/demolition sites. Clearly the field of view of the employed sensors has to be adequate for the target scene.

B. Dataset and labelling

CDW data collection under real world conditions as well as accurate labelling are required for precise classification, quantification, and characterisation of waste under the EWC standard, underpinning efficient waste valorisation. This methodology ensures accurate waste composition analysis, enhancing the accuracy of material segregation and quantification.

C. AI Models

Among the various AI models employed in the literature, the YOLO series emerges as a particularly powerful tool for object detection and segmentation. YOLO unifies class prediction and localisation in one stage detector, allowing the entire image to be analysed at once. This approach not only speeds up the detection process, but also reduces the chances of losing objects during analysis, making it an ideal solution for tracking objects in videos [19,39–41]. One of the most widely used models in the literature for segmentation is YOLOv8-seg. Its ability to process images quickly and accurately makes it the ideal choice for real-time object identification [42,43]. Its deep learning architecture, trained

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on a complete set of images taken in very similar contexts with respect to end-use can enable the recognition of various types of CDWs, which is crucial for effective waste management. This model has been chosen for the first test for the classification of the CDWs, as shown in Section III.

However, Mask R-CNN represents a viable alternative; it is based on and extends the architecture of Faster R-CNN by introducing an additional level of complexity to deal with the segmentation of instances. While Faster R-CNN focuses on the detection of objects and the prediction of their bounding boxes, Mask R-CNN adds a parallel branch for the prediction of pixel-level binary masks for each region of interest (ROI). Being a multi-stage detector, Mask R-CNN processes images through several stages, first identifying ROIs, then classifying and localising objects, and finally generating precise masks for each detected instance. This approach makes it particularly powerful for applications requiring granular detail [44,45].

For a more complete understanding of the scenarios of interest for the present work, the integration with LiDAR technology may be particularly appropriate. In fact, by incorporating point cloud data obtained from LiDAR, the approach goes beyond the simple detection, enabling an accurate quantification of waste volumes. The fusion of AI-model-based sensing with spatial data from LiDAR would allow for a more in-depth analysis of waste materials, identifying the type of material and estimating the related volume. This integration promises to improve the efficiency and effectiveness of waste identification and quantification processes, paving the way for more informed and sustainable waste management practices in construction and demolition operations.

As a more advanced approach, AI models exploiting imaging in both visible and IR can be used. By combining the detailed resolution of visible images with the detection of emission variations in thermal images, this innovative method can significantly improve the AI ability to recognise and classify CDWs in different environmental conditions. This capability is particularly useful for distinguishing materials that may appear similar in visible light but have different thermal properties.

III. Proof of Concept

The feasibility of the proposed solution has been preliminarily tested considering waste piles scenario and using a pre-trained CNN (i.e., YOLOv8-seg), re-trained with labelled data from online sources [46] to identify three main classes of wastes, namely concrete, rebar, and plastic (PVC). The dataset, consisting of 370 images, was divided into a training set (75%) and a validation set (25%) – 16% concrete, 38% plastic, and 46% rebar.

It is worth to notice that the datasets available online, although easily accessible, have several limitations, as it can be expected. In particular, the images contained are few in number and lack the variety and realism necessary to achieve satisfactory result. Therefore, the results of the present test must be interpreted with caution, as preliminary results. In fact, the performance of YOLOv8-seg, although promising in terms of its ability to identify and segment waste materials, was inevitably hampered by the shortcomings of the dataset, especially for the recognition of concrete, which is due to the non-balanced dataset across classes. However, it is crucial to consider this initial test as a stepping stone rather than a definitive assessment of the potential of the proposed approach.

Then, the trained model was tested on a few data collected in the first experimental campaigns carried out in the framework of the RECONSTRUCT project in two demo sites provided by COMSA Corporación (Barcelona, Spain) and Sorigué (Barcelona, Spain), investigating the trained model generalisation potential. In particular, this dataset equates to a total of 5579 images containing multiple material samples. Multiple scenarios of interest were identified based on specific activities including waste piles, truck, and waste containers. These were accordingly labelled with the aid of expert annotators (Fig. 3).

Fig. 4 shows examples of the CDWs recognition by the first model with the bounding box, typical of YOLO models, and the confidence levels. The main outcome of this phase is the validation of YOLOv8-seg as a valid tool for waste detection and classification. This test served as an important learning experience, highlighting the critical role of data quality in AI-driven waste management.

Fig. 3 Example of image annotation in the truck scenario. Labelling courtesy of Brunel University London.

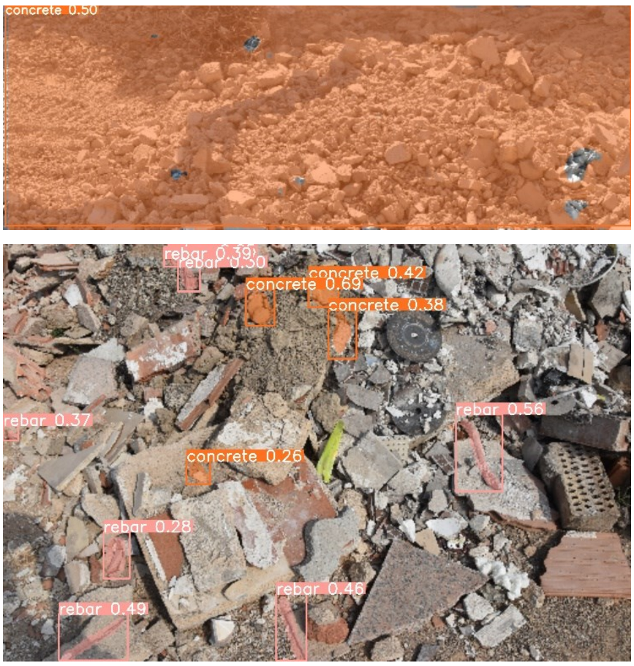

Fig. 4 First results from CDWs recognition, mainly considering concrete and rebars.

IV. Conclusion and Future Perspectives

In this paper a solution based on sensors and AI algorithms for CDWs recognition and valorisation has been proposed. This approach can be applicable in-field. The information inferred is exploitable for the automatization of CDWs detection, characterization, and, hence, sorting. An uncertainty analysis will be performed on the developed models to provide results with associated confidence intervals. This analysis will include both hardware and software parts of the entire pipeline for CDWs characterization, to characterize the whole measurement chain from a metrological point of view, also identifying the steps that could be improved. In this way, the final users can properly interpret and exploit the results, especially for valorisation purposes. This goes in the direction of enhancing sustainability and circularity in the construction sector, supporting CDWs valorisation and avoid that potential wastes remain so. Indeed, these solutions allow to give these materials an added value, providing information exploitable in platforms specifically dedicated to valorisation (e.g., Synerplatform) that are connected with a dense network of enterprises potentially interested in reuse such resources.

The proposed solution (including both hardware and software parts) will be validated in a few project demo cases, including both waste management sites and construction/demolition sites applications. Once it is deployed in the framework of the RECONSTRUCT project, it can be easily scaled to different applications (e.g., management of urban wastes). The interoperability of the proposed approach should be considered in order to make the process easily scalable and open to different applications and other sensors. For ease of scalability and interoperability, standards in force as well as semantics should be always considered [47]. The owners of both waste management sites and construction/demolition sites should be supported in raising their awareness on the potential benefits of these solutions, in order to widen their applications and taking advantage of new scenarios to improve the models performance the developed model(s) will be evaluated through standard metrics like accuracy, precision, recall, and F1 score.

The following tips can be considered for the development of solutions contributing to innovation in this field:

- Data-fusion considering multiple sensors working in diverse spectral regions can represent a good way to achieve a complete footprint of the materials for their classification;
- Real scenarios should be considered to obtain robust models. Datasets should be collected in real-life conditions, as close as possible to the final application;
- Data augmentation techniques (e.g., Fréchet Inception Distance method as employed by Na et al. [21]) could be used to widen the sample population and mitigate the noise effect typical of in-field applications;
- Smart segmentation techniques could be exploited to efficiently annotate datasets; zero-shot segmentation and SAM tools could be used as well as object detection features as suggested in [47].

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