COBOL: COmmunity-Based Organized Littering

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I. Introduction

Littering is a major problem that threatens the environment [4], the society and the economy [2]. Littering is not limited to urban areas, but it may easily turn sub-urban areas and countryside areas into rubbish dumps, destroying flora and fauna. Collecting this rubbish generates economic and social costs, as reported in [1], and some affected natural areas can be part of protected zones, which are considered tremendous assets for the regions. Keeping track, monitoring, and regularly cleaning littering sites can be a crucial problem, involving public authorities, municipalities, companies, and citizens. Previous approaches addressed this problem with either highly technological, but also expensive solutions (e.g., radar satellite images) [12] or with solutions that provide little support to the waste disposal process, while heavily relying on users committed to continuously submitting waste reports [5].

COBOL is a National project funded by the Italian MUR started in December 2023 with the aim of defining an advanced framework for managing the waste disposal process. COBOL involves three universities (the University of Milano - Bicocca, which coordinates the project, the Polytechnic of Milan, and the Gran Sasso Science Institute) and interacts with multiple Italian municipalities interested to experiment with the developed services. COBOL works on the definition of a decentralized data-processing architecture that exploits gamification to involve all the relevant stakeholders in the waste disposal process; model-driven engineering, to enable the creation of highly flexible and executable waste disposal models; computer vision, to help identify, sort and categorize the reported waste effectively; federated learning, to enable the sharing of knowledge among different communities involved in waste management without breaking privacy requirements; and self-adaptation, to ensure the capability to face unexpected events. Early results show that the federated learning architecture can be effectively used to collect reports and computer vision techniques applied to real-life datasets can be used to semi-automate the littering detection process.

II. The COBOL Approach and Architecture

Figure 1 shows the COBOL high level architecture. Citizens can contribute to littering reporting in two non-exclusive ways (bottom part of the figure): (i) *explicit*, users report geo-localized pictures of wastes through a dedicated mobile app; (ii) *implicit* by means of a lightweight detector running on devices that detects littering of any shape in the background of media (e.g., photos, videos), by estimating its volume and materials and allows for incremental learning, becoming more accurate as users use it. COBOL involves citizens in the *waste disposal process*, giving them information about the nature of the waste, the process to follow to remove and/or dispose it, and the contacts of the organizations that can dispose of the specifically detected waste when it could not be removed and brought to a landfill. When a new report is submitted to the system, the delivered data are analyzed by an engine identifying and managing the *self-adaptive waste removal process*. This component can understand the process suggested for waste disposal by interpreting the provided models. BPMN [8] models can be used to formalize the waste disposal process involving different stakeholders and procedures. COBOL establishes *gamified processes* for both citizens and administrations. Citizens are rewarded for reporting and removing waste, with the latter being rewarded the most. Citizens will be also rewarded for confirming or disproving waste removal actions taken by other actors. Based on citizens' reports, administrators will also compete in terms of their ability to keep areas clean, as demonstrated by some measured *Key Performance Indicators (KPIs)*. Generating *KPI dashboards* is a task that can be fulfilled by exploiting model-driven [11] and low-code [3] paradigms to enable custom visualizations based on the output of the processed modeled and interpreted. Finally, the reports and the metadata derived from their analysis are exploited to create a *Community-level image and data repository*. This enables the training of models for the automatic classification and detection of waste from pictures. In particular, to push learning to a new scale, COBOL exploits federated learning techniques to let multiple communities (e.g., multiple towns, cities, areas, etc.) share data, leveraging each other reports to generate better models faster, without breaking privacy. This strategy lets also small communities, which typically generate a limited amount of data (e.g., small towns in rural areas), to quickly accumulate knowledge exploiting an inter-community effort.

III. Early Results

This section anticipates some initial results that we obtained using the federated learning paradigm to collect data, on

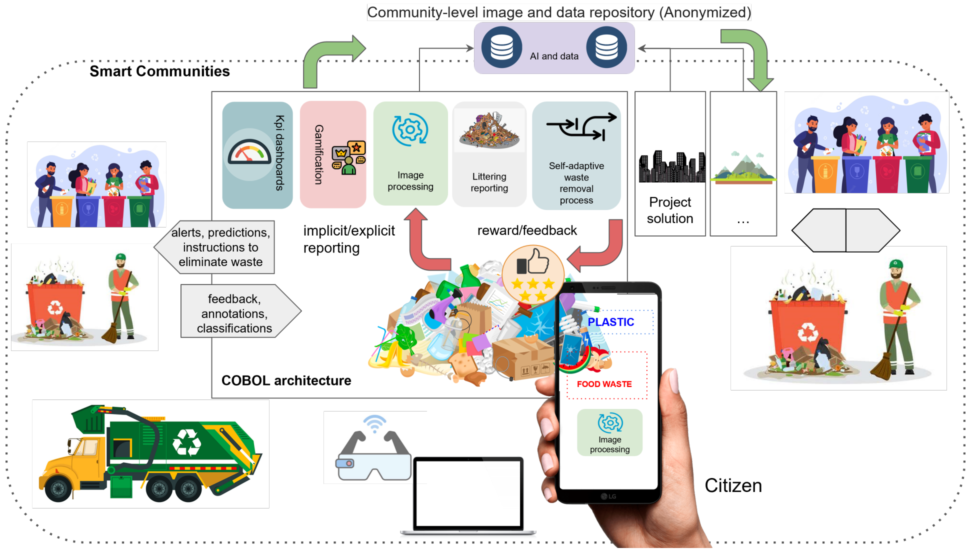

Fig. 1. Overview of the COBOL high-level architecture

computer vision techniques to detect litter, and on business process modeling to deliver adaptive processes.

A. On the use of the federated learning architecture

Our initial experiments aim at identifying a suitable federated learning framework to tackle the heterogeneity in both the data to analyze and the devices of the considered scenario.

We extended Flower (https://flower.ai as a reference platform. In the context of a larger experiment about federated learning [10], we carried out experiments with the MNIST datasets [7], model architectures (MLP, CNN), and heterogeneity levels. We mimicked 100 concurrently active nodes and 200 training rounds, which resemble a COBOL community of reasonable size. The results demonstrate the effectiveness of dynamic node selection to improve accuracy, but also witness the impact of dynamic workload management, but with an impact on accuracy. A suitable compromise between these two aspects is key for an efficient and accurate operation of the FL infrastructure. With the MNIST dataset on MLP architecture, the dynamic selection of nodes allows us to increase accuracy (from 0.941 to 0.955) after 200 iterations, and the loss drops from 0.233 to 0.016. In contrast, if we compare static workload allocation and ECT (our worst case) the accuracy drops from 0.946 to 0.920, the loss increases from 0.207 to 0.346, but the minimum training time drops from 20.70 to 4.67 sec.

B. On littering detection with computer vision techniques

We preliminary investigated the feasibility of performing automatic littering detection using the TACO dataset [9], which is an open image dataset for litter detection and segmentation containing 1500 images and 4784 annotations belonging to 60 different categories hierarchically organized in 10 super-categories. In our experiments we face the so called TACO-1 task, i.e. classless litter detection where the goal is to only detect litter items. As detector we train the smallest and fastest model in the YOLOv5 family [6], i.e. YOLOv5n with a total of 1.9M parameters, which could be used in citizens' devices to detect litter. The performance of the trained litter detector in terms of mean average precision at an intersection over union threshold of 0.5 is mAP50=0.522, which is in line with the expected drop in performance observed in other tasks with respect to the larger models (e.g., YOLO-v5s with a total of 9.1M parameters). Analyzing the per-class performance, we can observe how the worst litter detection performance are obtained on litter classes having a small physical size as for example cigarette butts, pop tabs, and straws, which have a low impact on our application. Overall, these results suggest the feasibility of automatically collecting and classifying litter with the COBOL framework.

C. On the Runtime Process Modeling

The littering reporting system can be assimilated to a crowdsourcing function that is able to report a littering situation and based on pre-defined rules gives feedback on how to apply a removal process or involving other public entities in the process. For this reason, we started to work on a crowdsource application exposing REST APIs for interacting with the basic functionalities of the system. Given this variability and the multi-entities nature of the removal and management process, we envisaged a process-model-based solution for designing the waste removal processes. We are currently exploring process modeling solutions like Camunda[1] with the intent of having a process model distributed interpreter that can interact with the reporting system APIs and based on the input parameters, e.g., type of waste, actors, etc, can run different processes that are stored in a distributed model repository. This would allow decision-makers to model their processes with the appropriate variability and trigger the right management based on the scenario.

[1]https://camunda.com/

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