Container inspection automation: a proof of concept

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Theme 6: Artificial intelligence (could also match **Theme 2**)
Abstract: *This work presents a POC for automated visual inspection of shipping containers thanks to a deep learning model (YOLOv5) trained to detect defects inside the container using videos collected by a rover. It was tested at a container depot in Asia. Several takeaways on the challenges faced during the project will be shared during the talk from historic data exploration on a big set of images, data collection and preparation, prioritization of the defects to detect for the POC, to labeling and modeling on a small dataset.*
Key words: container inspection, rover, video defect detection, yolov5, data collection, labeling.

1. Introduction: The inspection of shipping containers at container depots is a major logistic challenge as it requires considerable resources (time and human). In fact, hundreds of containers are visually inspected everyday by surveyors who take close up pictures of detected defects (corrosion, dent, spill…) with tablets, categorize them following a rigorous norm (there are more than 100 types of defects) and recommend repair or cleaning actions. One container's inspection can take approximately 5 (no defects) to 40 minutes (serious defects) and about 30% of containers are expected to suffer from some damages. A possible way towards container inspection automation is to be able to detect and classify their interior and exterior defects using computer vision models applied to video streams from cameras positioned in a way that ensures the defects' visibility. This work presents a Proof Of Concept (POC) for this strategy focusing on interior defects detection.

2. Methodology: Two initial steps were key to this project. On the one hand, a rover was identified as the best option to collect videos inside containers. For this POC, the workflow was the following: a surveyor opens the container's doors, puts the rover inside it and controls it. Our team recommended a typical rover path inside the container in order to ensure maximal visibility of the defects. On the other hand, among 20 interior defect types, the top priority defects to detect during this POC were selected through exploration and analysis of: (1) the historic pictures taken by the surveyors during their inspections and (2) the distribution of the newly collected defects by the rover. The defect types' selection was based on three criteria: expected visibility on rover videos, high occurrence in historic and newly collected data, high business value. For a few weeks, inspectors followed the data collection procedure we defined and labeled the data at the same time. To do so, we extracted images from the videos and deployed an open source labeling tool: LabelStudio. Since the most straightforward modeling option to detect defects in this context is object detection, we trained inspectors to use LabelStudio and draw bounding boxes around the defects. It was crucial that the inspectors do it themselves because the categorization of the defects requires a high level of expertise. In order to respect the project timeline, the data collection had to stop in spite of the fact that a lot of defect types were highly underrepresented and the number of samples very low. The object detection model proposed was trained on 5 types of defects using a medium yolov5 architecture pretrained on the COCO dataset and data augmentation. The data splitting procedure was designed so that the original data distribution was respected in each data subset and data leaks avoided (eg: no images from videos of the train set are used in the test set). The performances are promising in spite of the data volume. They vary according to the number of collected samples for each defect type (from 70% to 25% of accuracy).

3. Conclusion: The originality of this work resides in the fact that this project covered all the steps of an artificial intelligence POC from framing (hardware selection, data collection, prioritization, labeling…) to modeling (in spite of a very small dataset) and performance evaluation. Our talk will be the opportunity to share takeaways on the challenges we faced during these steps, especially data collection and labeling. For future work, we expect to collect more data, maximize the automation of the data collection by the rover, focus on exterior defects detection and deploy all the defect detection models at a container depot in Asia. On the modeling side, we could test object detectors based on Transformers and the corresponding interpretability tools for a more efficient results analysis.