Co-UDlabs

Building Collaborative Urban Drainage research Labs communities

MS16 Report - Open Access Coding/Images for Automated detection of in-pipe defects in CCTV sewer surveys

Date of delivery – 28/07/23

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N°101008626

DOCUMENT TRACKS DETAILS

Project acronym	Co-UDlabs
Project title	Building Collaborative Urban Drainage research labs communities
Starting date	01.05.2021
Duration	48 months
Call identifier	H2020-INFRAIA-2020-1
Grant Agreement No	101008626

Document Information	
Milestone Report	MS16
Work package number	7
Report title	Open Access Coding/Images for Automated detection of in-pipe defects in CCTV sewer surveys
Lead beneficiary	UFSD
Author	Ehsan Kazemi, Simon Tait
Due date	31/07/2023
Actual submission date	28/07/2023
Type of document	Report
Dissemination level	Public

VERSION MANAGEMENT

Revision history and quality check			
Version	Name	Date	Comment
V 0.1	E Kazemi	23/06/23	Draft
V 0.2	S Tait	26/07/23	Format changes, additional background material
V 0.3	S Tait	28/07/23	Submit to co-ordinator

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Background: about the Co-UDlabs Project

Co-UDlabs is an EU-funded project aiming to integrate research and innovation activities in the field of Urban Drainage Systems (UDS) to address pressing public health, flood risks and environmental challenges.

Bringing together 17 unique research facilities, Co-UDlabs offers training and free access to a wide range of high-level scientific instruments, smart monitoring technologies and digital water analysis tools for advancing knowledge and innovation in UDS.

Co-UDlabs aims to create an urban drainage large-scale facilities network to provide opportunities for monitoring water quality, UDS performance and smart and open data approaches.

The main objective of the project is to provide a transnational multidisciplinary collaborative research infrastructure that will allow stakeholders, academic researchers, and innovators in the urban drainage water sector to come together, share ideas, co-produce project concepts and then benefit from access to top-class research infrastructures to develop, improve and demonstrate those concepts, thereby building a collaborative European Urban Drainage research and innovation community.

The initiative will facilitate the uptake of innovation in traditional buried pipe systems and newer green-blue infrastructure, with a focus on increasing the understanding of asset deterioration and improving system resilience.

List of acronyms

Acronym / Abbreviation	Meaning / Full text
CCTV	Close circuit television
DL	Deep Learning

1. Executive summary

The primary method for defect identification and classification is based around using CCTV to collect images and then these are used for subsequent analysis. In the later analysis images are normally manually inspected and defects are classified according to a standard classification. The defect classification methods used in European countries are different, but have a similar structure, which reflects their historical development and is described in EN13508:Part2. The current national defect classification schemes are generally complex involving a large number of defect codes. Considering the various defect classification codes across Europe the number of unique defect codes is now greater than 300. In contrast in Japan the defect coding system contains just 10 defect types. There are a number of academic studies and more recent companies that are developing data-driven classifiers to link observed defects with a defect classification code. These studies have shown some promise but have resulted in collection of large numbers of images.

This milestone report describe the outcome of work to consider what knowledge could be gained from a more straightforward defect classification approach.   This report presents a deep-learning based framework for the automated detection of in-pipe defects in closed-circuit television (CCTV) sewer surveys. The framework utilizes the Ultralytics YOLO v8 model for image processing and defect detection. By eliminating the need for manual feature extraction, this approach simplifies the identification of defects that are challenging to extract features from, such as those found in sewer pipes. The report outlines the methodology, demonstration results, and provides recommendations for further work. All the source code is open access and has been developed to a standard to encourage other, especially non-specialists in small companies and utilities to try and investigate whether a more simplified defect classification scheme can provide the knowledge needed to enhance their management of buried sewer assets. All the code is publically available, with sample images and written software support to allow ease of access. The team at Sheffield will continue to develop this open access approach to software development and encourage those that use the code and uploaded images to report on their findings.

2. Introduction

In the water industry, the timely detection of in-pipe defects is crucial for maintaining efficient and reliable sewer systems. CCTV inspection is the most popular technique used to locate and identify individual defects, this data is then used to assess sewer condition. Decisions on sewer rehabilitation and replacement are often based on the condition data obtained from the analysis of CCTV images. About ten years ago studies in the Netherlands e.g. Dirksen et al. (2010) reported that the manual inspection of CCTV images could lead to two types of error. In the first defects were missed and in the second defects were not recorded accurately. Manual inspection also was the major cost element of sewer inspection. Dirkesen et al. (2010) also demonstrated that the introduction of a more complex sewer defect classification standard led to higher levels of defect mis-identification.

There have been a number of studies on automated defect detection using classical computer vision methods such as colour thresholding and feature extraction. Recently, more advanced computer vision models have used deep learning (DL) without the need for a separate phase of feature extraction. For example, Myrans et al (2019) used a Random Forests based approach to identify defect types as specified in the UK's sewer classification system. This approach classified the probability of a defect (type) in an image using a collection of RF algorithms trained on image data for specified defect types. The highest ranked defect was then assigned to that frame. Using case study data this approach was able to correctly identify different defect types from 86% for joints, to 20% for holes. It is clear that the approach's reliability varied strongly with defect type. This work is continuing with the use of larger and larger image training sets.

A different approach was used in this work. Firstly a simplified defect classification system was proposed and then an automated based image approach proposed. This approach was tested with data obtained from water utilities. This milestone report introduces an automated approach based on deep learning, which eliminates the need for manual feature extraction, making it particularly suitable for complex defect identification in sewer pipes. It also examines the potential for utilising simpler defect classification methods to assess whether a DL method combined with a simpler defect classification method could provide useful information to water utilities.

The code and the underlying training and validation data are open source and available via github. The aim being to encourage others (non-specialists) to investigate the potential for using such an approach.

3. Approach

The classification of in-pipe defects plays a crucial role in effectively addressing maintenance and management of sewer networks. These defects are categorized into five distinct classes in this report, arranged in descending order of importance, as outlined in Table 1. Each class encompasses several subclasses, which provide further granularity by considering factors such as the defect's position, size, or condition. A recent DWA survey described that "Intruding or defective connections" (27.3 %) followed by "Fissure" (25.7 %) and then displaced joints (18.9%) were the most frequent type of structural pipe damage. Blockage was the most common operational defect. The simpler classification was determined based on evidence such as this and should reflect the impact and source of each defect, Table 1.

- Blockage: common operational defect that reduces flow capacity and increases flood risk.
- Intrusion: artefact that reduces flow capacity and increases flood risk
- Joint: physical artefact of many sewer pipes
- Crack: artefact showing evidence of minor structural damage
- Sever damage: a group of defects that indicate the loss of structural integrity

These classification types were used to define images that were used to train the developed DL model.

To train the deep learning (DL) model for automated defect detection, a set of labels, as presented in Table 2, is employed to annotate the CCTV images. These labels, comprising eight categories, are not directly tied to the defect classes or subclasses but have been formulated based on the characteristics observed during DL image analysis. The DL model relies primarily on shape and colour attributes to accurately recognize and classify the objects (defects) within the images. In order to mitigate the influence of colour, which does not significantly contribute to the defect classification, a preprocessing step is performed wherein the images are converted to grayscale before being utilized for model training.

Regarding shape analysis, the DL model demonstrates an ability to identify objects with similar shapes, regardless of their dimensions. However, if there are significant differences in shape, they are considered distinct objects. For instance, within the defect classification outlined in Table 1, intrusions are classified as a single class. However, it should be noted that an intrusion can manifest as either a pipe or a tree root, exhibiting entirely different shapes. To account for this distinction, the labelling system within the DL framework assigns intrusions to two separate categories, namely 'ObsPlc' and 'ObsRot', representing pipes and tree roots, respectively, as depicted in Table 2.

Conversely, certain defects, such as cracks, encompass multiple subclasses within the defect classification provided in Table 1. However, for DL analysis, only a single label, denoted as 'Crk', is defined. When the DL model successfully detects a crack, it becomes necessary to employ additional specialized models to accurately quantify the number of cracks, measure their sizes, and determine their positions within the image. This subsequent analysis enables the mapping of detected cracks to their respective subclasses within the defect classification scheme. For other defect types, also, such post analyses are necessary to be able to map the detected defects to the classes in Table 1.

Table 1. Classifications of sewer in-pipe defects.

<table>
<tr><th>No.</th><th>Class</th><th colspan="3">Subclasses</th></tr>
<tr><td rowspan="3">1</td><td rowspan="3">Blockage (deposits / attached deposits)</td><td colspan="3">Small</td></tr>
<tr><td colspan="3">Medium</td></tr>
<tr><td colspan="3">Large</td></tr>
<tr><td rowspan="6">2</td><td rowspan="6">Intrusion (defective connection, pipe, root)</td><td rowspan="2">Small</td><td colspan="2">Upper part of pipe section</td></tr>
<tr><td colspan="2">Lower part of pipe section</td></tr>
<tr><td rowspan="2">Medium</td><td colspan="2">Upper part of pipe section</td></tr>
<tr><td colspan="2">Lower part of pipe section</td></tr>
<tr><td rowspan="2">Large</td><td colspan="2">Upper part of pipe section</td></tr>
<tr><td colspan="2">Lower part of pipe section</td></tr>
<tr><td rowspan="2">3</td><td rowspan="2">Joint</td><td colspan="3">Undamaged</td></tr>
<tr><td colspan="3">Damaged</td></tr>
<tr><td rowspan="9">4</td><td rowspan="9">Crack</td><td rowspan="6">Longitudinal</td><td rowspan="2">Small</td><td>Dangerous position</td></tr>
<tr><td>Not dangerous</td></tr>
<tr><td rowspan="2">Medium</td><td>Dangerous position</td></tr>
<tr><td>Not dangerous</td></tr>
<tr><td rowspan="2">Large</td><td>Dangerous position</td></tr>
<tr><td>Not dangerous</td></tr>
<tr><td rowspan="3">Circumferential</td><td colspan="2">Small</td></tr>
<tr><td colspan="2">Medium</td></tr>
<tr><td colspan="2">Large</td></tr>
<tr><td rowspan="3">5</td><td rowspan="3">Severe damage</td><td colspan="3">Hole</td></tr>
<tr><td colspan="3">Broken / fractured</td></tr>
<tr><td colspan="3">Collapsed</td></tr>
</table>

Table 2. Labels used for DL model training.

Label	Label Name	Map to classifications in Table 1.
Obstacle – Block	ObsPlc	Measure size of obstacle after DL detection
Obstacle – Tree Root	ObsRot	Measure size of obstacle after DL detection
Obstacle – Sediment Deposition	ObsDep	Measure size of obstacle after DL detection
Joint	Jnt	Measure thickness of joint after DL detection
Crack	Crk	After DL detection, count number of cracks in the image and measure size and position of them
Damage – Hole	DmgSev	Directly mapped
Damage – Severe (Broken, Collapsed)	DmgSev	Measure / compare cross-section of pipe after DL detection

Condition assessment approaches, particularly in the EU have become more complex to apply especially by including (i) estimates of likelihood and scale of consequence and occasionally intervention costs. The original idea of condition grades was to aggregate complex visual observations of in-pipe defects into a single numerical “aggregated” grade. Current inspection capabilities (CCTV, with mainly manual interpretation) mean that all assets cannot be inspected in a timely fashion. This lack of data and knowledge has led to the need to develop deterioration models. Given the lack of repeat defect inspection data a knowledge gap is how individual in-pipe defects develop. Currently asset databases have a relatively small number of defect observations taken at a relatively low frequency. So there is little empirical evidence as to how defects develop. Some defects, e.g. joint displacement may develop slowly and continuously before resulting in sudden failure. Others such as a crack may be created and then suddenly fail as local stresses are concentrated by this type of defect. There is a need to collect data on pipe defects that make of a large proportion of in-pipe defects and also have a high impact when they fail

4. Methodology

To enable the automated defect detection, the Ultralytics YOLO v8 framework is employed (available at https://github.com/ultralytics/ultralytics, accessed on 13/06/2023). This robust system processes images and facilitates the training of models that can effectively identify and locate defects. The project GitHub repository (https://github.com/Co-UDlabs/sewer_defects, accessed on 13/06/2023) provides a comprehensive guide, complete with instructions on data preparation, image labelling, model training, and usage, along with the relevant source codes.

For image labelling, YoloLabel v1.2.1 (accessible at https://github.com/developer0hye/Yolo_Label, accessed on 13/06/2023) is utilized. The process of labelling is demonstrated in the accompanying video, which can be found at the following link: https://drive.google.com/file/d/1CTeDLK8DkOE8SMFm0joFSnadAJ92aY35/view?usp=drive_link (accessed on 13/06/2023). In this video, instances of defects are easily labelled using a rectangular bounding box defined by four vertices, ensuring accurate annotation.

Within the repository, two models specifically cater to camera calibration and object size estimation. These models, being further developed for sewer pipes, serve as valuable resources for mapping the detected defects to the classifications defined in Table 1.

To showcase the functionality of the three models, several examples are provided at https://github.com/Co-UDlabs/sewer_defects/tree/coudlabs/coudlabs/examples (accessed on 13/06/2023). Additionally, exemplar input data necessary for running these examples are conveniently located in a Google Folder, accessible through the following link: https://drive.google.com/drive/u/1/folders/1BoLSWbCj6WimaW4-Wca3CPkpgW5HJUqH (accessed on 13/06/2023).

By leveraging the capabilities of the Ultralytics YOLO v8 framework, coupled with the provided guidelines, image labelling tools, and pre-prepared models, the detection of defects within unseen pipes can be automated with precision and efficiency. These resources contribute to advancing defect analysis and maintenance practices in sewer systems, ultimately leading to more frequent and possibly better quality data to understand defect development. Another advantage of a simpler classification approach is that it can better focus the manual inspection of existing CCTV data in identifying the location of all defects, their simple grouping and so allow inspectors to focus on what they consider to be key defects.

5. Preliminary Results

The dataset shared via the aforementioned Google Drive link serves as a limited-scale demonstration of the model's functionality. It should be noted that the labelled images within the dataset are free from any copyright restrictions and can be utilized without constraint. In order to train our model, this dataset was combined with a portion of the publicly available Sewer-ML Dataset[1] (not included in the Google Drive folder). A total of 1,577 images captured from sewer pipes were annotated to identify defects. The distribution of incident occurrences for each label specified in Table 2 is graphically represented in Figure 1. It is worth mentioning that the dataset does not contain any instances of pipe corrosion, hence the additional 'Cor' label has no corresponding data within the current dataset. Figure 2 provides a visual depiction of the positional coordinates and dimensions of the bounding boxes encompassing the labelled defects.

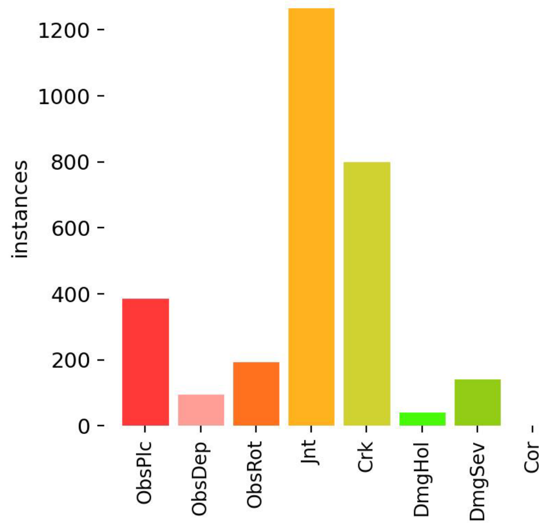

Figure 1. The number of instances of the labelled defects in the training dataset.

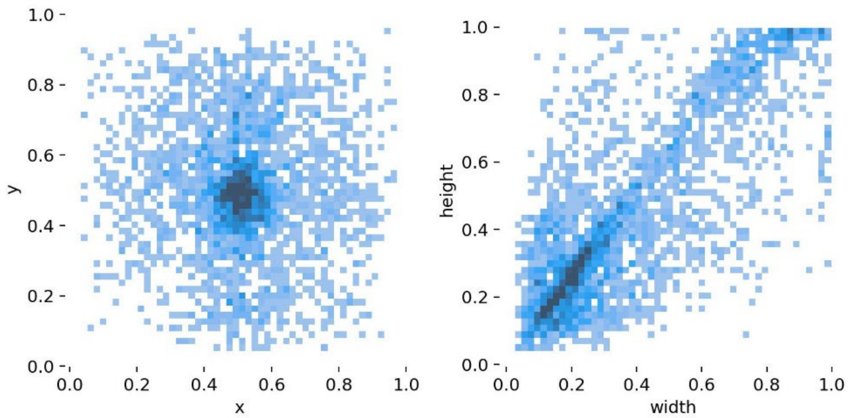

Figure 2. Position of the centre of the bounding boxes and their width and height for all the defects in the pipes.

[1] Haurum and Moeslund (2021) Sewer-ML: A Multi-Label Sewer Defect Classification Dataset and Benchmark. Available at https://vap.aau.dk/sewer-ml/ (accessed on 13/06/2023)

The dataset was partitioned into three distinct subsets for the purposes of training, validation, and testing, with proportions of 75%, 15%, and 15%, respectively. Figure 3 presents the Precision-Recall curve obtained from training the model using 75% of the data, allowing for an analysis of the model's accuracy across different defect types.

In Figure 4, a selection of labelled images employed for training and validation is showcased, while Figure 5 demonstrates the model's corresponding predictions on this dataset. The accuracy metrics for the training and validation phases are calculated based on the disparities between the positional coordinates and sizes of the bounding boxes employed during training and those predicted during validation.

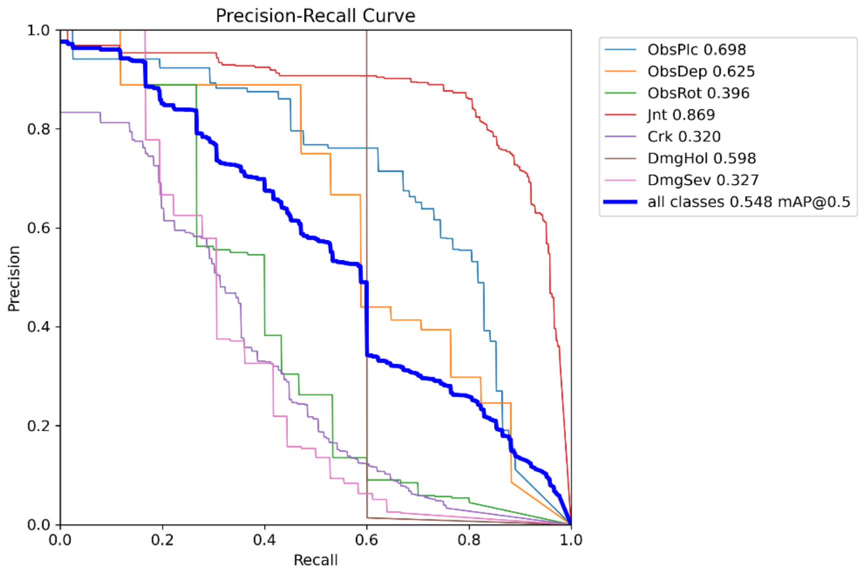

Figure 3. Precision-Recall of the model training. This is based on still images.

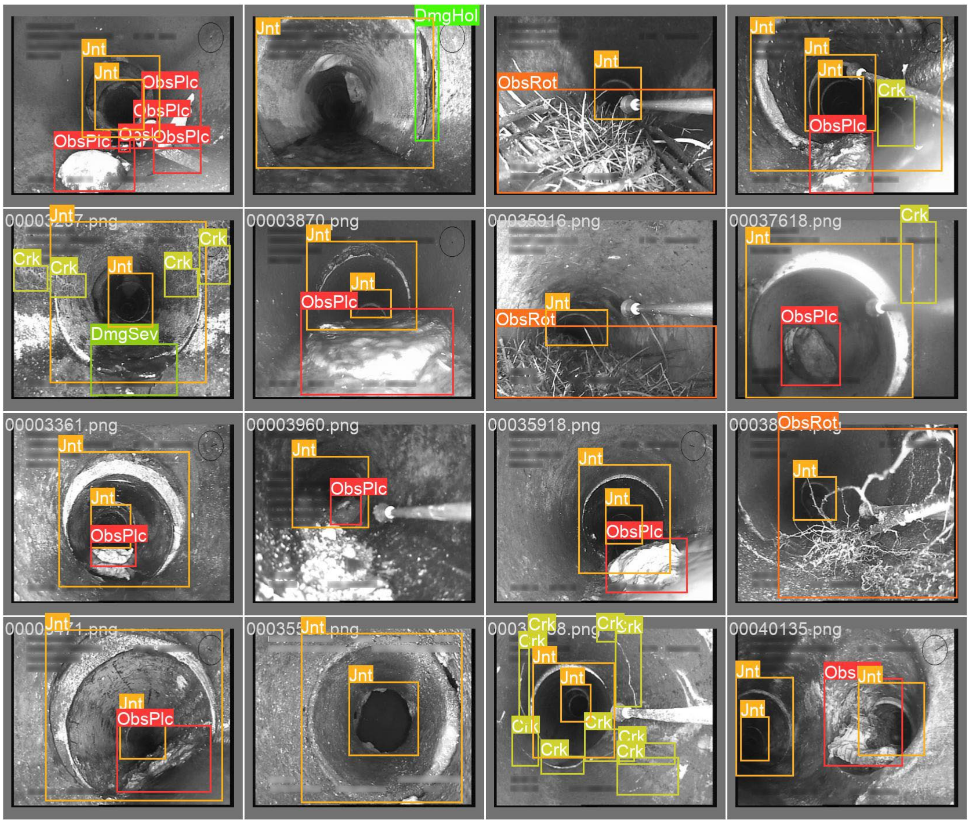

Figure 4. Labels in some of the images used to validate the model.

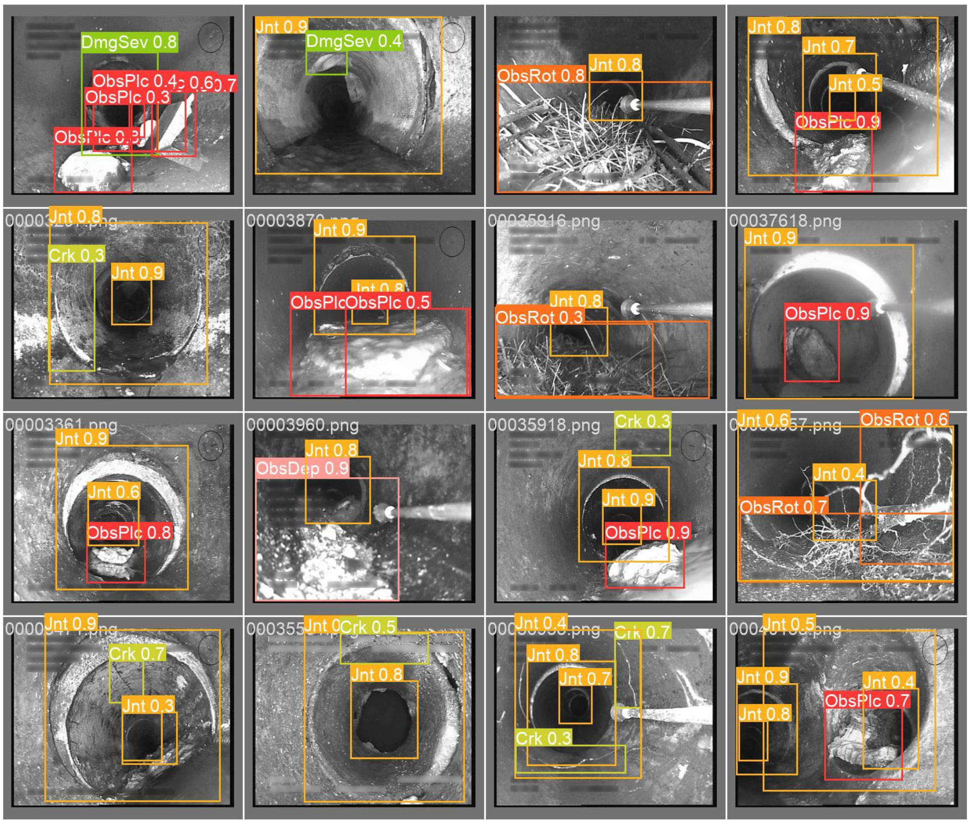

Figure 5. Predictions by the model of a part of the validation set shown in Figure 4.

Subsequently, the trained model was utilized to predict and detect defects within a set of previously unseen images, constituting 15% of the overall data. Figure 6 provides several examples showcasing the model's predictions, with the numerical values displayed above the respective bounding boxes indicating the confidence level of each detection, which ranges from 0 to 1.

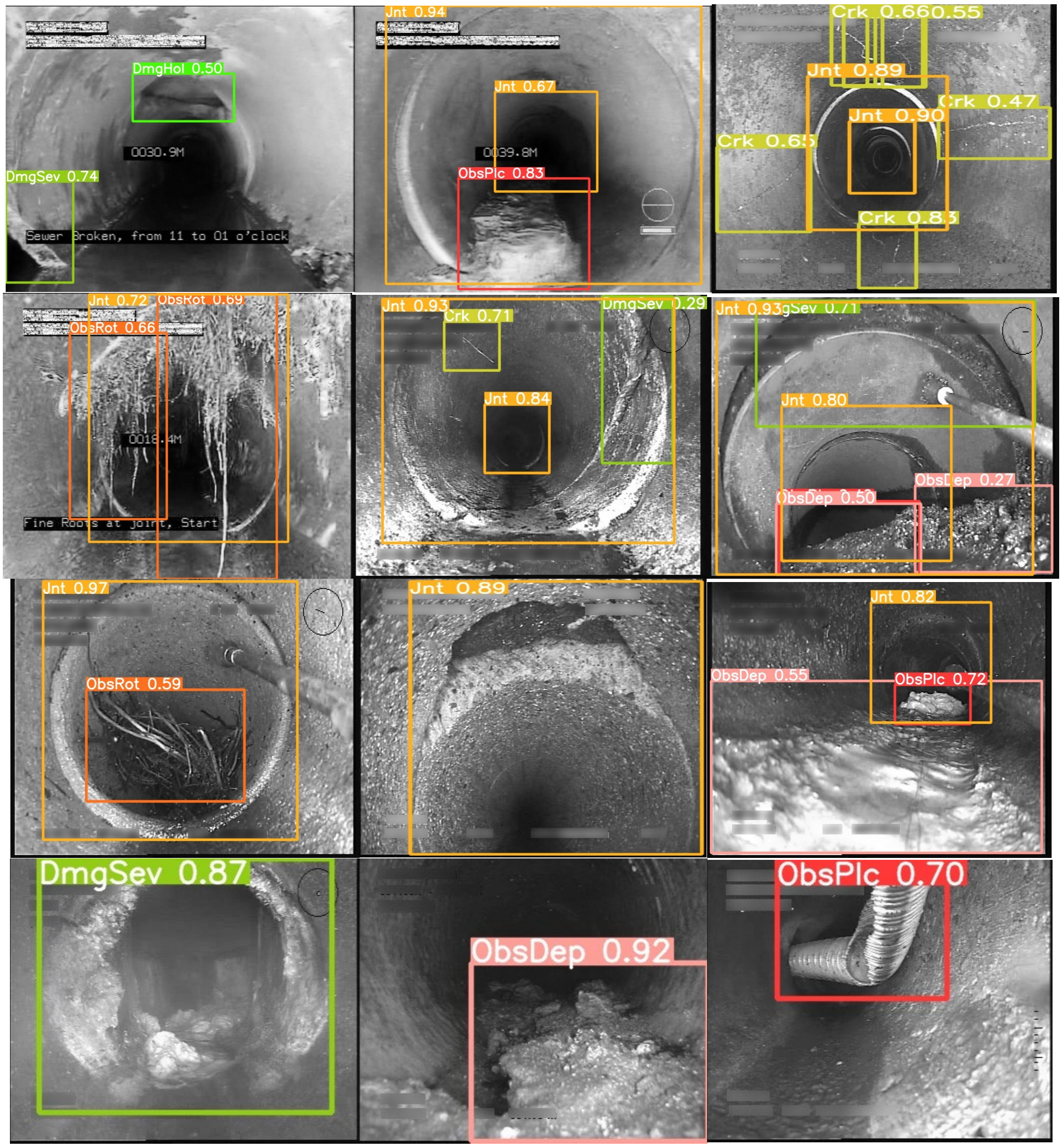

Figure 6. A few examples of the results of the defect detections using the trained model.

When employing the model for defect detection in videos, as opposed to static images, it becomes crucial to establish a methodology for enhancing the confidence of predictions based on the sequential nature of image frames. If the model identifies a specific defect across multiple consecutive frames, it signifies a heightened level of confidence in the prediction. To achieve this, predetermined thresholds must be established concerning the number of successive frames and the minimum prediction confidence required. For instance, if the same defect is detected in 30 consecutive frames with a confidence level surpassing 0.5, it is highly probable that an actual defect exists, thus warranting further inspection.

6. Further Developments

The team at Sheffield are continuing to develop the work in the following ways:

- Collect more data of cracks and damages to enhance the model's training and performance.
- Review and refine the definitions, as well as clarify the distinctions between different obstacle types, i.e. ObsPlc (block obstacle), ObsRot (tree root), and ObsDep (sediment deposition).
- Explore the utilization of different versions of pre-trained YOLO models, which can be found on the following page: https://docs.ultralytics.com/models/yolov8/#supported-tasks (accessed on 13/06/2023).
- Fine-tune the hyperparameters of the YOLO model specifically tailored to the requirements of the current application. Detailed information on this process can be found here: https://docs.ultralytics.com/usage/cfg/#train (accessed on 13/06/2023).
- Evaluate the effectiveness of image filtering techniques during the preprocessing step of the Defect Detection Model. This may involve experiments with conversion to greyscale and the implementation of noise reduction methods.
- Enhance the Defect Size Estimation model, ensuring improved accuracy in real-world scenarios.

7. Conclusions

An open access github site has been developed that contains well-structured and supported code to analyze CCTV sewer inspection images. The code support and open license is to ensure that others can use, investigate and develop the code as they wish.

A simplified defect classification was proposed that grouped defects on their impact rather than their visual appearance.

The deep learning-based framework presented in this report offers a promising solution for the automated detection of in-pipe defects in CCTV sewer surveys. By leveraging the Ultralytics YOLO v8 model and eliminating the need for manual feature extraction, this approach simplifies and enhances the accuracy of defect identification.

The preliminary results demonstrate the effectiveness of the framework, and further development steps are outlined to improve its performance and expand its capabilities.

Please note that all the links provided in this report are subject to availability and may change over time. Although this is not the intention of the authors. If changes are made to these links they will be communicated through the CoUD_Labs project website.

8. References

BS EN 13508-2:2003 Condition of Drain and Sewer Systems outside buildings. Visual inspection coding systems. British Standards Institute, www.bsi-global.com, updated 2007, and 2011.

Dirksen J., Clemens F.H.L.R, Korving H., Cherqui F., Le Gauffe P., Ertl T., Muller K., Snaterse T.M. (2013) The consistency of visual sewer inspection data. Structure and Infrastructure Engineering 9(3), 214-228, doi: 10.1080/15732479.2010.541265

Myrans J., Everson R., Kapelan Z. (2019) Automated detection of fault types in CCTV sewer surveys, Journal of Hydroinformatics, 21(1)153-163, doi: 10.2166/hydro.2018.073