Defect detection in Sewer Pipes Using Deep Learning

Focus op Vision

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Introduction

The proper functionality of underground sewer pipes is vital for the civil infrastructure of cities. Sewer systems are prone to many types of defects, which lead to massive consequences for the society:

- Exposure to sewage gas
- Spreading of diseases
- Flooding of surfaces

To avoid the mentioned inconveniences, it is important to track and monitor the condition of the sewer systems. This project introduces the research question "Is it feasible to detect defects in sewer pipes using deep-learning with convolutional neural networks?".

Materials and Methods

For this project, the materials and methods used were the following:

- Dataset of 1000 samples, extracted from provided annotated videos
- Data Augmentation of horizontal/vertical flips, rotations, and zooming
- The main metric of measurement is Intersection over Union

The main defect to be detected for this iteration of the project was infiltration, as pictured in Fig. 2.

Abstract

The functionality of sewer pipes is important in order to avoid social problems and the spread of diseases. For that purpose, the project tackles the research question "is it feasible to detect defects in sewer pipes using deep-learning with convolutional neural networks". Taking a dataset of text-annotated videos videos and annotating them by hand, 1000 samples of infiltration defect were concluded. Splitting 60% train, 20% validation and 20% testing for experiments with two networks – U-Net and Mask-RCNN. After training the networks and performing validation, U-Net resulted in 0.85 IoU score, while Mask-RCNN 0.71, which is a 0.14 score difference. Hence it is concluded that defect detection in sewer pipes is possible with the use of U-Net.

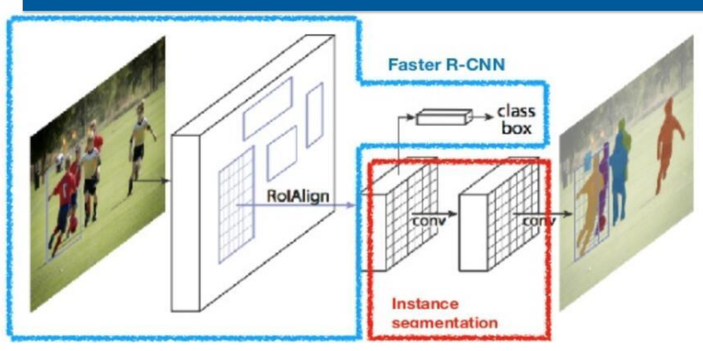

Figure 1. Mask-RCNN architecture used in the project

The dataset used for the experiments was gathered with the following steps:

- Initial 13 videos of varying length between 8-20 minutes provided, with text-annotations of the defects
- Frames of infiltration defects extracted – 1000 final samples
- Split the 1000 samples for 60% training, 20% validation and 20% testing
- Annotated training and validation datasets using LabelMe with polygons due to the varying forms of infiltration defects

Figure 2. Example image defect – infiltration, outlined in green on right and left – raw example

Experiments and Results

Experiments have been performed using two neural networks: Mask-RCNN and U-Net. Further pre-processing steps such as data augmentation and grayscale conversion of images has also been tested. The result from the training is found in the following table:

Results				
Model	**Class**	**Mean IoU**	**Validation Loss**	**Loss**
U-Net	Infiltration	**0.85**	0.73	0.05
Mask-RCNN	Infiltration	0.71	1.84	0.30

Table 1. Experiment results

- The aforementioned networks were trained for 150 epochs
- Training steps equal to the size of the training set
- Fig. 3 shows inference of U-Net (blue) and Mask-RCNN (red)
- Mask-RCNN achieved a mean IoU of 0.71 on the validation dataset
- U-Net achieved a mean IoU of 0.85 on the validation dataset
- Due to being more lightweight, U-Net trained approximately 4 times faster than Mask-RCNN

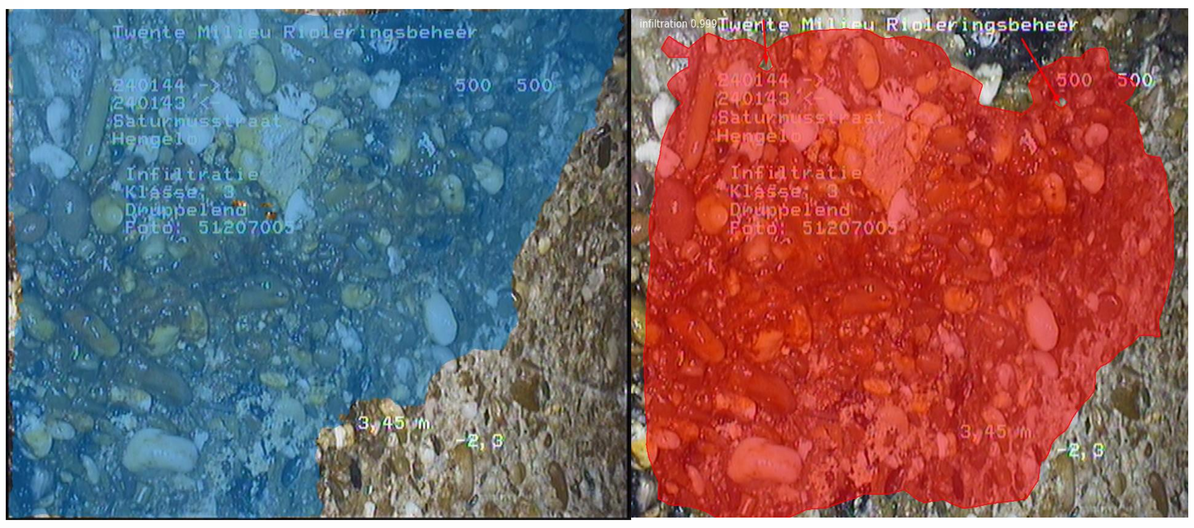

Figure 3. U-Net (blue) and Mask-RCNN (red) inference results

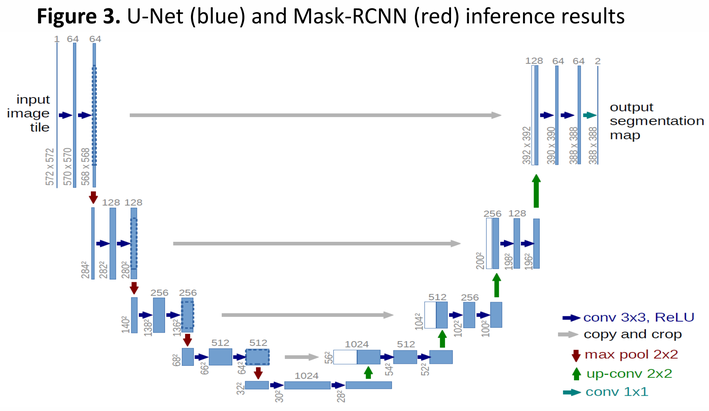

Figure 4. U-Net (blue) architecture used in the project

Conclusions

Based on the results achieved by the performed experiments, it is concluded that U-Net, with an IoU score of 0.85, has more precise predictions and performs training and inference faster than Mask-RCNN, 0.71 IoU, due to being a more lightweight network. The current version of the Mask-RCNN experiment will need further work to be considered a success, such as enlarging the dataset, hyperparameter tuning and better annotations. U-Net could be improved by experimenting different architectures, changing the threshold value for capturing defective areas and longer training period. Finally, the research question is concluded that it is possible to detect defects in sewer pipes using convolutional neural networks, in this case U-Net.

Acknowledgements

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