Comparison of deep learning approaches to monitor trash screen blockage from CCTV cameras

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Motivation

Trash screens are tools used to prevent debris and people from entering critical parts of a river network:

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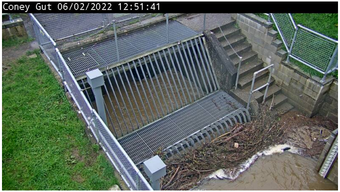
Clean trash screen



Blocked trash screen

Debris can pile up at the screen and block the waterway and provoke floods

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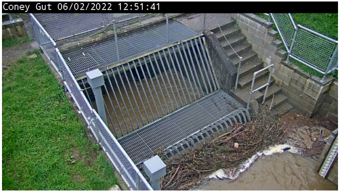

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- Manual observation is tedious

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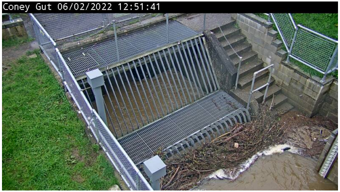

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Our goal: propose deep learning based methods to automate the monitoring process

Dataset

South-West Environment Agency website:

- 54 trash screens with CCTV camera feeds
- 70,000 images downloaded over 10 months (Feb - Nov 2022)

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Manual labelling of the images using a small Python script

- Three possible labels: *clean*, *other* and *blocked*

clean

other

blocked

- 40,000 *clean* images; 10,000 *blocked* images; 20,000 *other* images

Methodology

- 46 training cameras, 4 validation cameras, 4 test cameras
- Test cameras chosen manually
  - Good balance between *clean* and *blocked* images
  - Different fields of view

Crinnis

Mevagissey

Barnstaple

Siston

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Compare deep learning approaches to detect the blockage

Constraint: one global model (no retraining per camera)

1. Generic methods

The model is directly applied on the new trash screen camera

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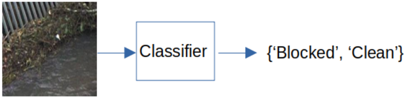
Classification



ResNet-50 backbone

- Trained over *blocked* and *clean* images
- Outputs a confidence score for *blocked* and *clean* categories

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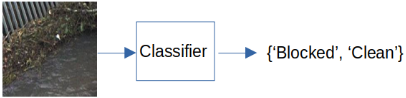
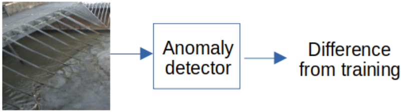
Anomaly detection

Classification





ResNet-50 backbone

- Trained over *blocked* and *clean* images
- Outputs a confidence score for *blocked* and *clean* categories

State-of-the-art method (Padim[1]):

- Trained over all images
  - No labelling needed
- Each image is represented by a vector of features
- Outputs the difference with training images

[1] Defard et al. *Padim: a patch distribution modeling framework for anomaly detection and localization.* ICPR, 2021

1. Generic methods: results

	Classifier	Anomaly Detector
Crinnis	92.15%	83.33%
Mevagissey	95.08%	70.06%
Barnstaple	90.42%	83.46%
Siston	70.98%	73.97%
Average	87.16%	77.71%

- Classifier obtains the best results
- Outperforms the state of the art based on predictions from river parameters[2] (74% accuracy).

[2] Streftaris et al. *Modeling probability of blockage at culvert trash screens using Bayesian approach.* Journal of Hydraulic Engineering, 2013.

2. Camera-specific methods

Takes advantage of labelled images from the new camera

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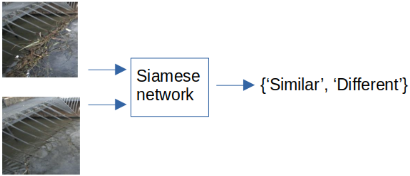
Image similarity



Siamese network

- Computes the difference between two images of the same camera
- *Different* if one is blocked and the other is clean, *Similar* otherwise
- Labelled images of the new camera are used as reference images

Camera-specific methods: results

	Siamese Network			Anomaly detector		
	N=1	N=5	N=50	N=1	N=5	N=50
Crinnis	94.30%	99.05%	99.43%	93.54%	94.72%	98.19%
Mevagissey	96.70%	96.91%	96.93%	80.14%	83.63%	75.51%
Barnstaple	96.05%	95.66%	96.39%	77.16%	77.34%	67.82%
Siston	90.42%	95.86%	96.48%	87.25%	91.83%	93.32%
Average	94.37%	96.87%	97.31%	84.52%	86.88%	83.71%

N is the number of labelled images from the camera

The siamese network greatly increases the results, even with N=1

- Same backbone as the classifier
- Smaller improvements after N=5

Conclusion

Efficient new approach to monitor trash screen blockage

- Quickly detects the blockages
- Benefits from a few number of labelled images from the camera (5 or less)

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Future work

- Night-time monitoring
- Provide more information (e.g., % of trash screen surface blocked, water-level,...)
- Practical integration

Department for Environment Food & Rural Affairs

Environment Agency

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Sharing is encouraged

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