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Automated Detection of Crack Features in Nuclear Plant Superheaters with Automatically Labelled Datasets

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Outline

- Project introduction
- Challenges in this project
- Automated labelling technique and classification
- Result discussion
- Conclusions

Introduction

- Typical anomalies in nuclear power plant components:

Corrosion on a pipe flange [1]

Crack in a steel component [2]

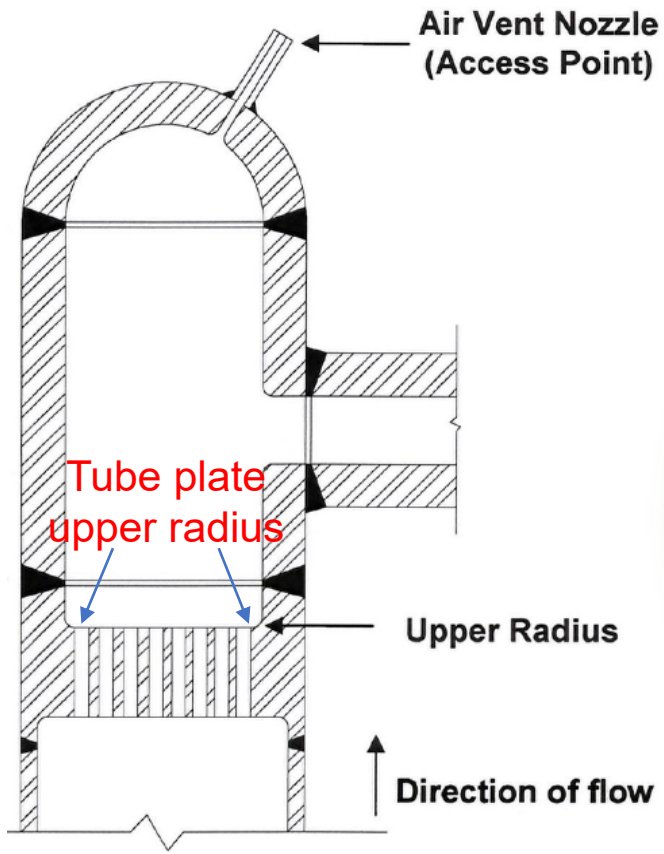
- Assurance of the normal condition of components is necessary for safe continued operation

[1] URL: https://www.shutterstock.com/search/flange+corrosion

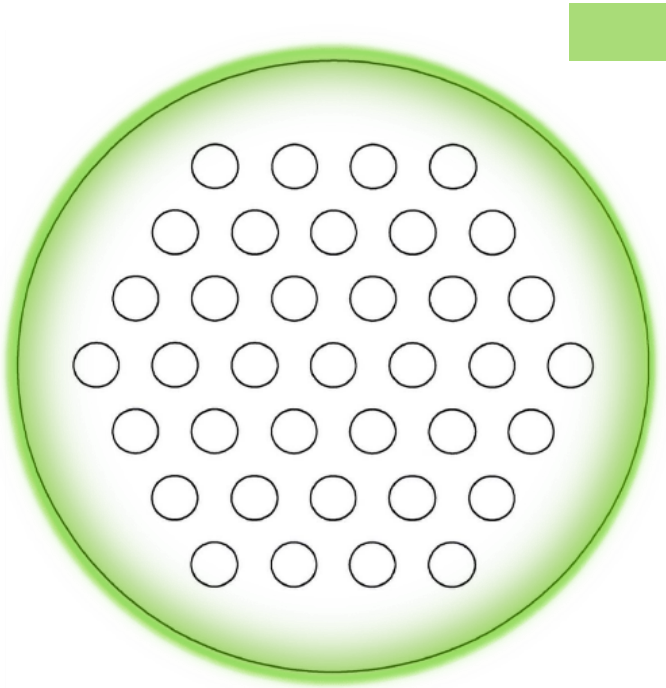
[2] T. Liu et al., Metallurgical analysis on a cracked super duplex stainless steel flange, *J Fail. Anal. and Preven.*, 14, 470–477 (2014)

Introduction

- Our case : Crack-like feature detection in superheaters



Superheater cross-sectional view [3]



Superheater tube sheet plain view [3]

[3] C. Kelly, “Superheater header tube sheet, tube sheet radius and boiler tube inspections”, EDF ENERGY internal report, Technique Sheet Number: BI222/HRA-HYA/004, Revision: 007 (2018).

Introduction

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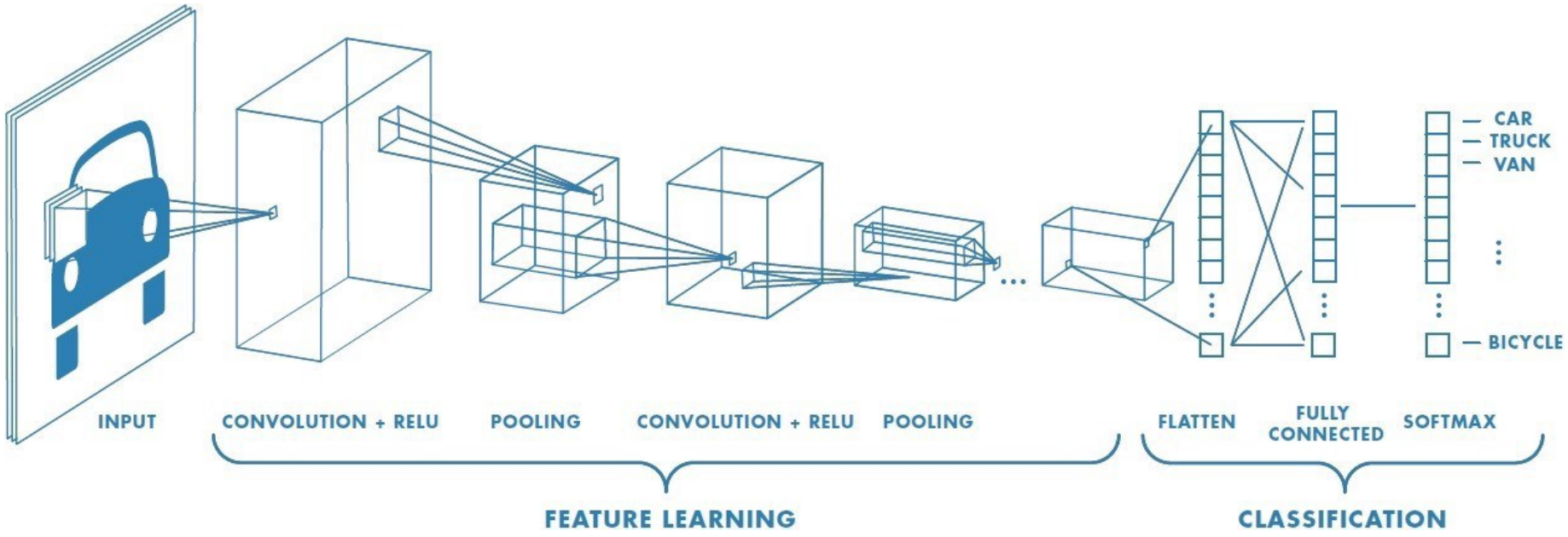
- Problem of interest
  - Manual visual inspection process may be prone to:
    - Large volume of inspection data (~hours)
    - Manual assessment is:
      - Laborious
      - Repetitive
      - Lengthy
- Research question
  - Can automated anomaly detection offer improvements in:
    - Accuracy ?
    - Efficiency ?
    - Speed ?

Introduction

- Classification technique: convolutional neural network (CNN)
  - Automatically learn features from training images and use learnt features to classify new images



Typical CNN structure [4]

[4] URL: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Challenges in our project

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- Large datasets are required to train the classification system
  - In published crack detection tasks:
    - 5,326 crack images were used automated crack detection in mock-up nuclear reactor cores in [5]
    - 32,000 crack and non-crack images were used for automated crack detection in concrete surfaces in [6]
    - 21,410 crack images were used for automated crack detection in pavement surfaces in [7]

[5] F. C. Chen and M. R. Jahanshahi, "NB-CNN: deep learning-based crack detection using convolutional neural network and Naïve Bayes data fusion," *IEEE Transactions on Industrial Electronics*, Vol.65, no.5, pp.4392-4400 (2018)

[6] Y. J. Cha, W. Choi, and O. Büyüköztürk, "Deep learning-based crack damage detection using convolutional neural networks," *Computer-Aided Civil and Infrastructure Engineering*, Vol.32, no.5, pp.361-378 (2017)

[7] B. Li, K. C. P. Wang, A. Zhang, E. Yang, and G. Wang, "Automatic classification of pavement crack using deep convolutional neural network," *International Journal of Pavement Engineering*, Vol.21, no.4, pp.457-463 (2020)

Challenges in our project

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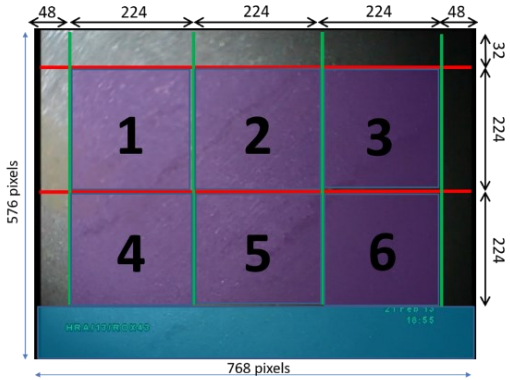
- Large datasets are required to train the classification system
- Challenges in manual labelling:
  - Very time consuming (30 x 25 x 6 = 4500 patches to manually label for a 30s clip)
  - Using same patch location may lead to learning “lighting” features rather than crack-like features
  - Consistent labelling of ambiguous crack features is difficult



(a) (b) (c)

- A consistent and efficient labelling technique is needed!

Automated labelling technique

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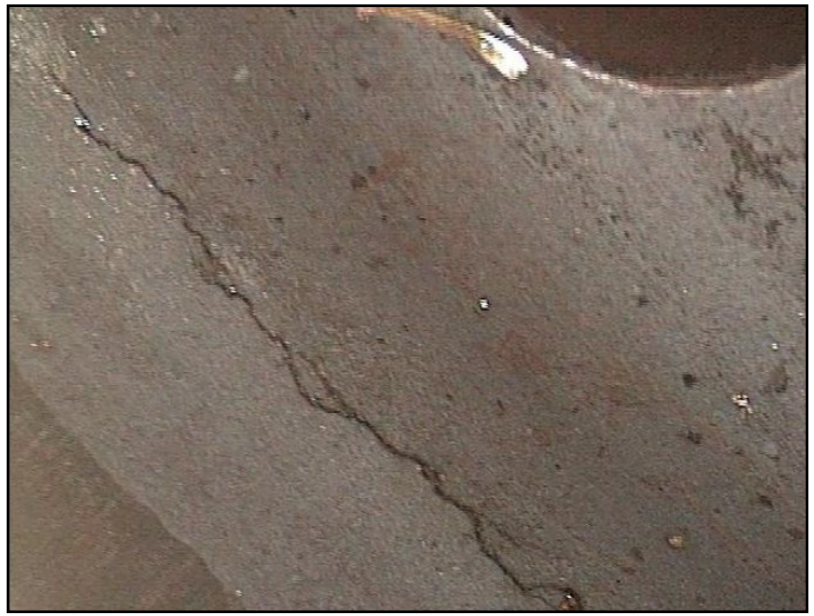
- How to perform automated labelling?
  - Create “binary mask” of the frame with crack-like features
  - Generate patches at random positions
  - Judge whether the crack intensity in the patch exceeds the predefined threshold



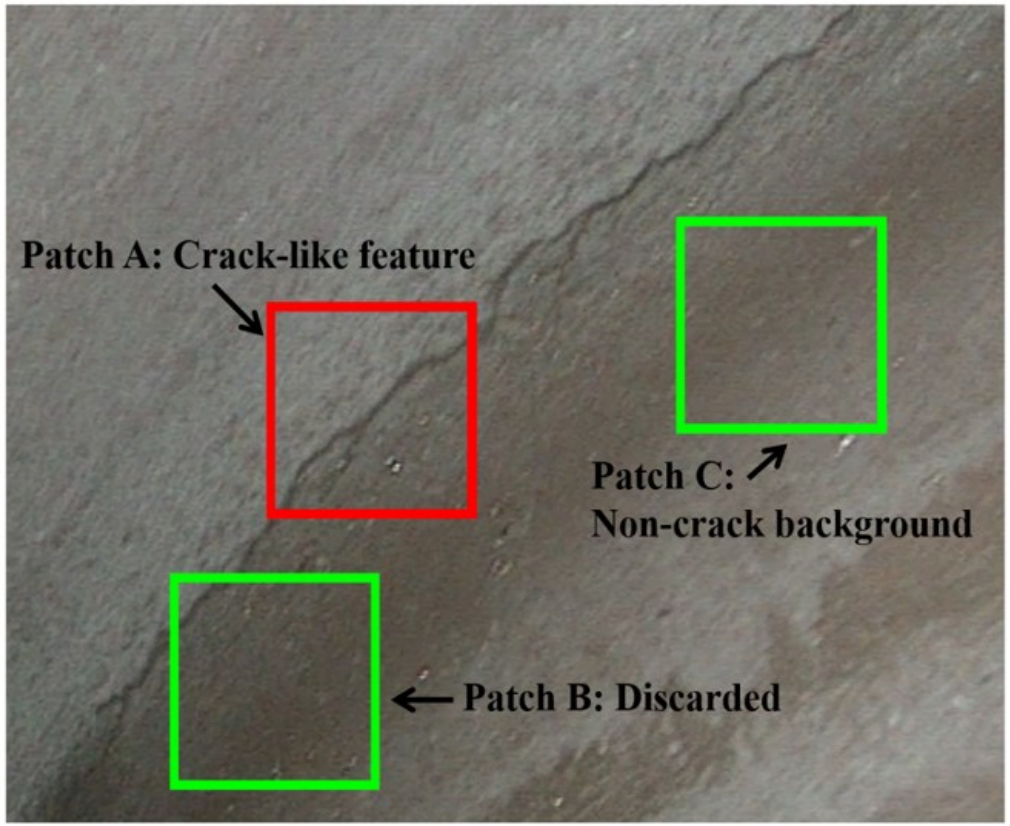
Ground-truth frame

0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	1	0	0	0
0	0	0	0	0	0	0	1	1	0	1	0	0

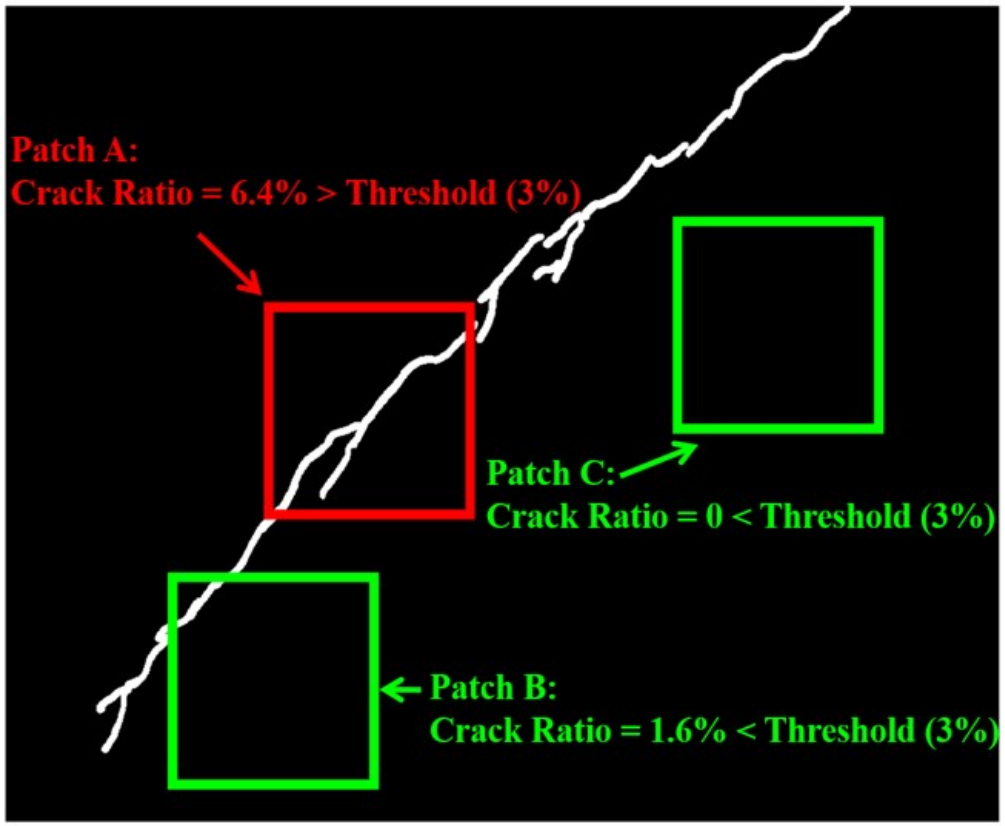
Binary mask

Automated labelling technique

- Example of automatically labelled patches



Ground-truth frame [8]



Binary crack mask [8]

[8] Z. Fei, G. West, P. Murray and G. Dobie. "Automated generation of training dataset for crack detection in nuclear power plant components," in *Proc. 12th Nuclear Plant Instrumentation, Control and Human-Machine Interface Technologies (NPIC&HMIT 2021)*, June 2021, pp. 251-258

Automated labelling technique

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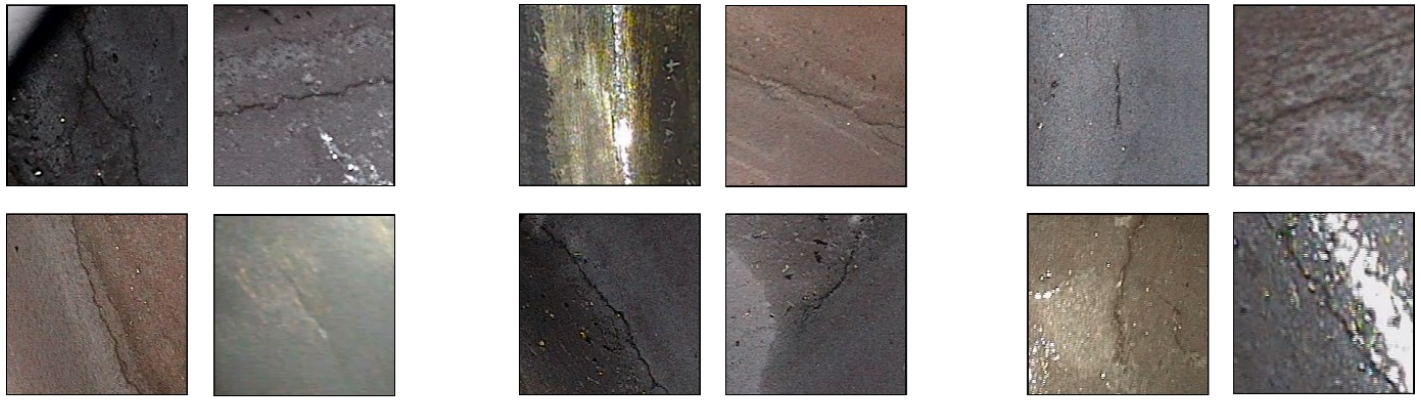
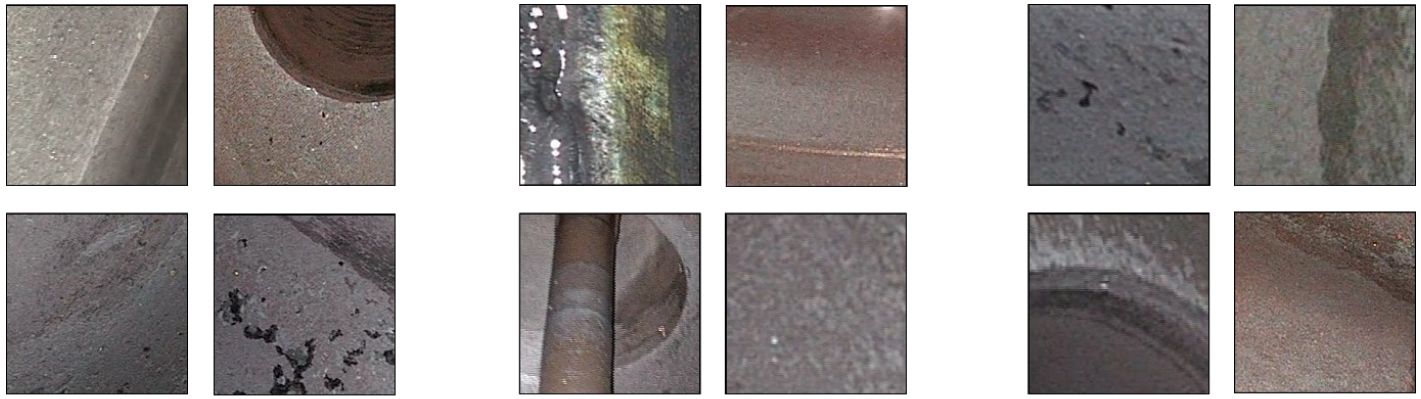
- Examples of “crack-feature” patches:



(a) (b) (c)

- Examples of “non-crack background” patches:



(a) (b) (c)

(a): Training dataset. (b): Validation dataset. (c): Testing dataset.

Classification system based on GoogLeNet

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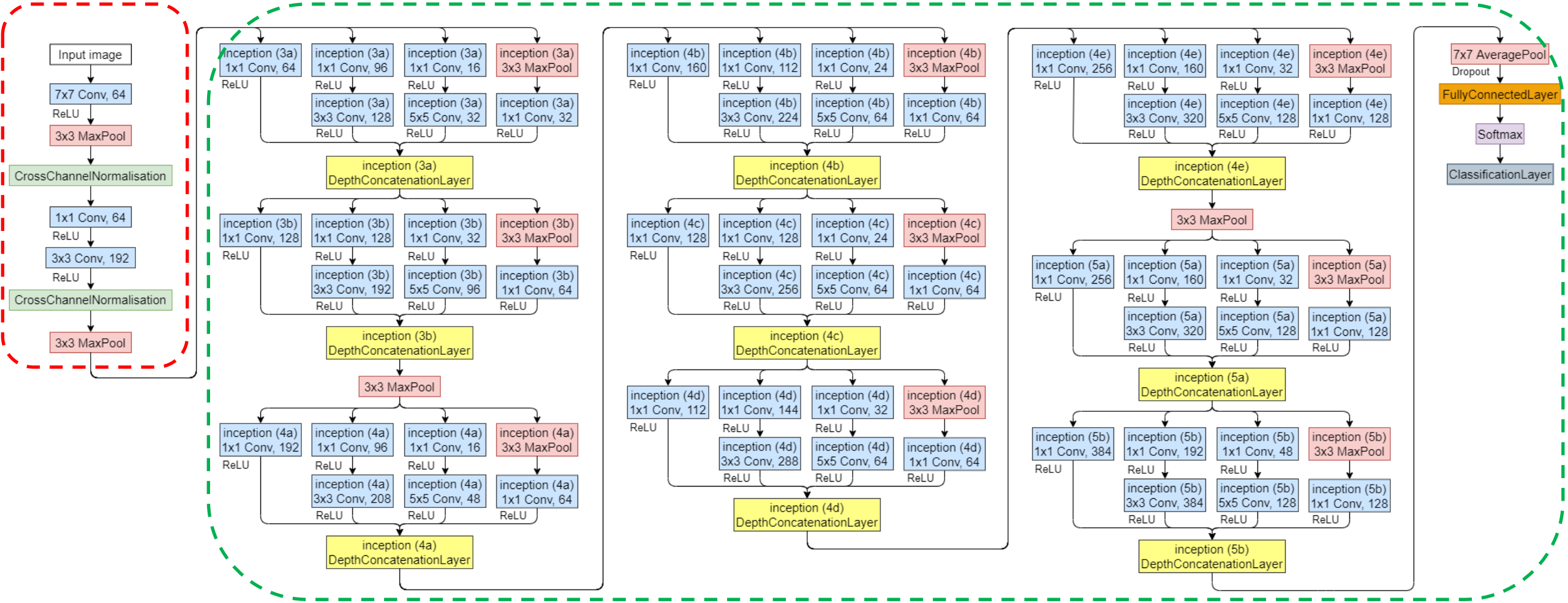
Frozen

Learnable



GoogLeNet architecture in MATLAB

Classification system

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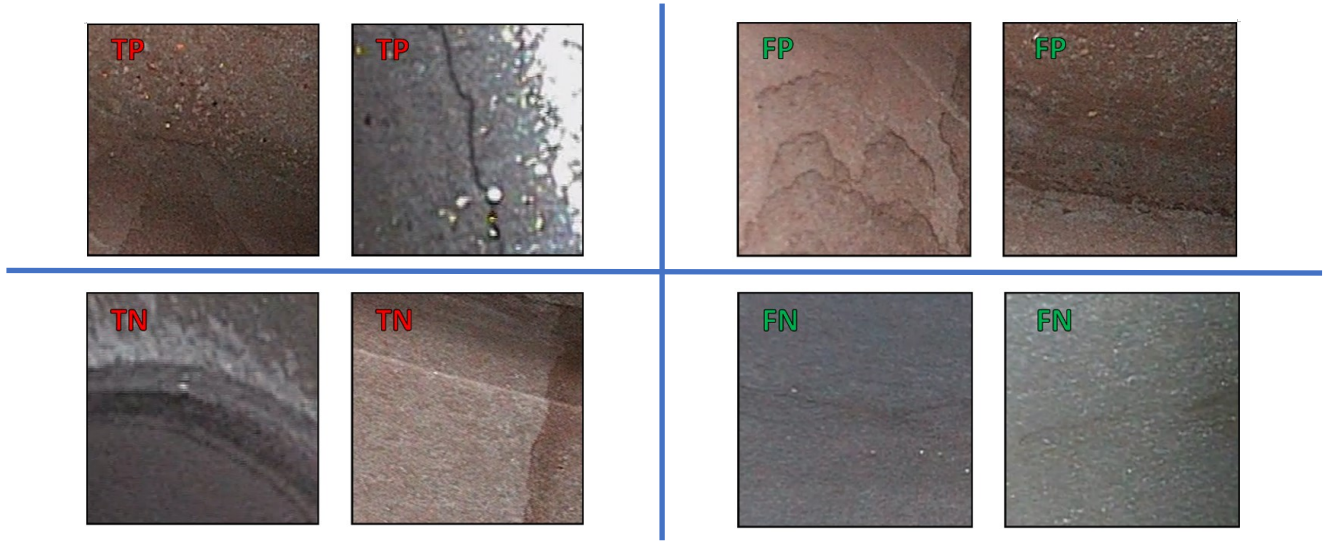
- Applied the transfer learning technique based on the pre-trained deep learning network (i.e., GoogLeNet)
- Good detection accuracy on the testing dataset:

Precision	Recall	F1 Score	Overall accuracy	TP	TN	FP	FN
94.6%	91.1%	92.8%	93.0%	175	182	10	17

- Examples of classified patches:



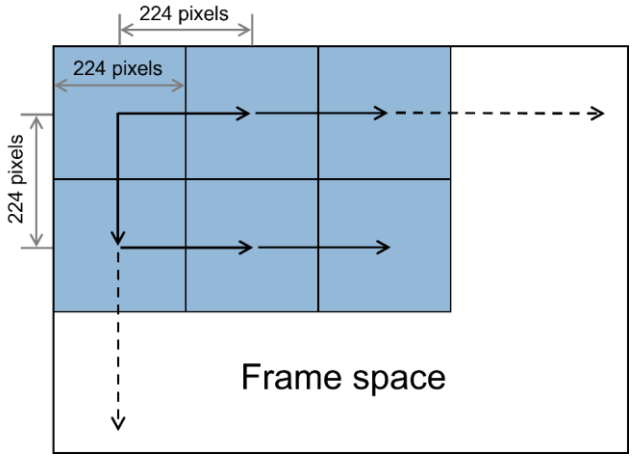
TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative.

Classification system

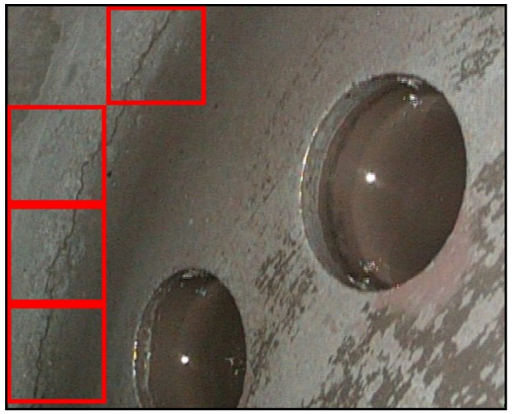
- Applied the transfer learning technique based on the pre-trained deep learning network (i.e., GoogLeNet)
- Good detection accuracy on the testing dataset:

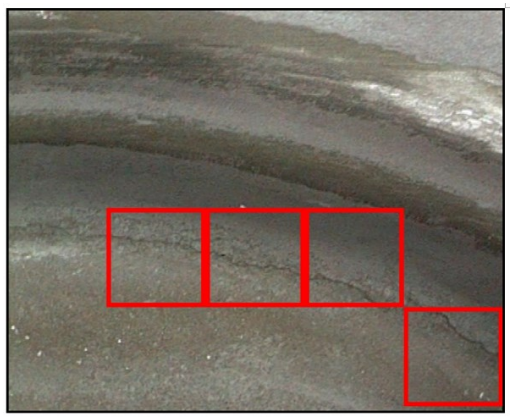
Precision	Recall	F1 Score	Overall accuracy	TP	TN	FP	FN
94.6%	91.1%	92.8%	93.0%	175	182	10	17

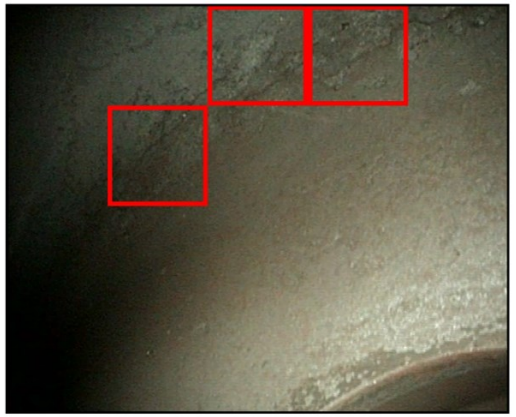
- Examples of automatically detected crack feature areas in testing video frames:



Full-grid scanning plan



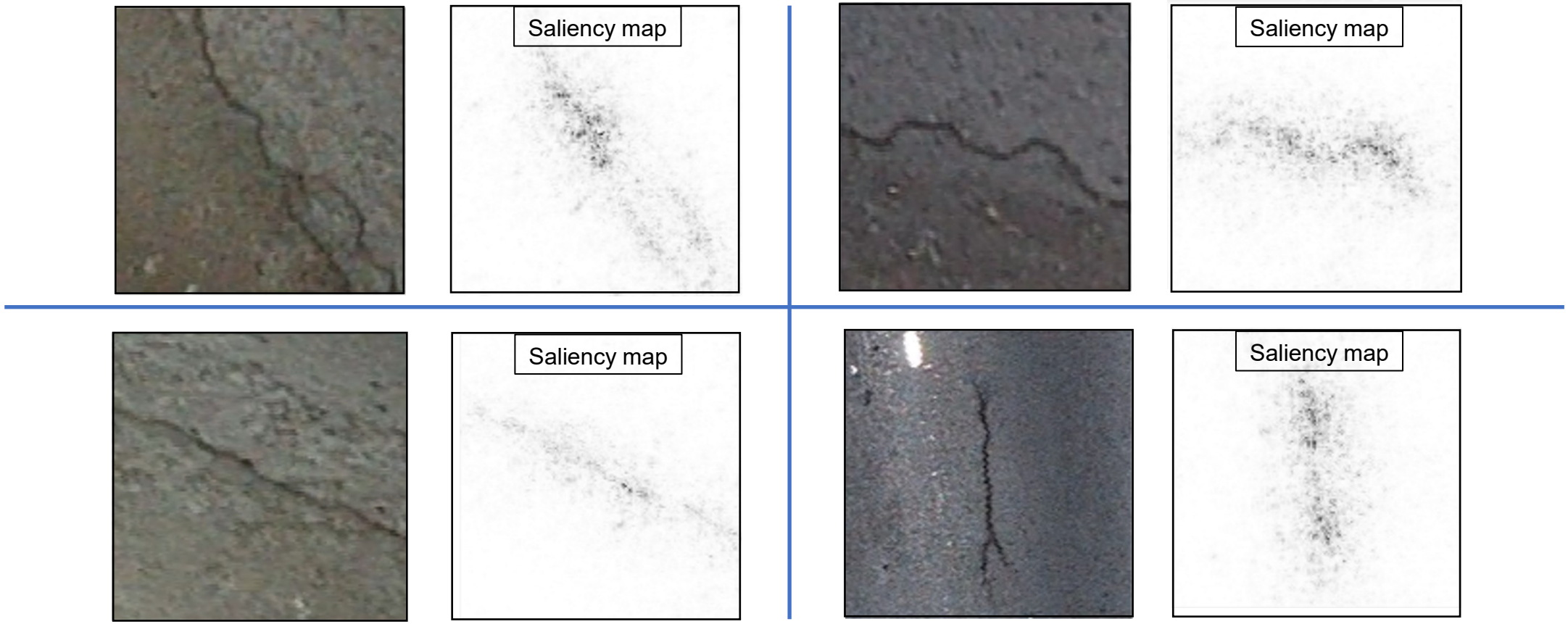




TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative.

Explicability of classification results

- Technique: Saliency Map based on guided propagation [9].
  - A pixel resolution map showing which pixels are most important to the classification, by computing the gradient of the class score with respect to the input pixels.



[9] K. Simonyan, A. Vedaldi, and A. Zisserman. "Deep inside convolutional networks: Visualising image classification models and saliency maps." *ArXiv:1312.6034 [Cs]*, April 19, 2014. http://arxiv.org/abs/1312.6034.

Conclusions

- Challenges of automated anomaly inspection in nuclear power plant components have been explained.
- The mechanism of the automated labelling technique for efficient generation of datasets has been presented.
- The automated crack detection system obtained using the automatically labelled datasets has been demonstrated and discussed.

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