Rail surface defect detection and severity analysis using CNNs on camera and axle box acceleration data

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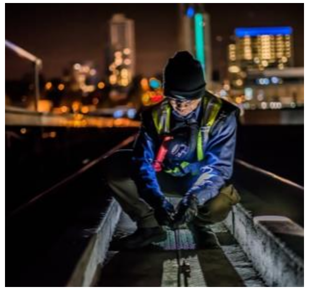
Motivation

- Infrastructure accounts for approximately one-third of the railway’s operating costs.
- Significant amount is related to labor-intensive maintenance.



- Ad hoc interventions are needed when faults occur → costly and disruptive

- Inspection is carried out by dedicated inspection cars or by track workers (foot patrols)

- Manual assessment of inspection data is time-consuming and prone to human errors.

Objectives

- Reduction of maintenance costs through digitalization and automation
- LCC reduction through condition-based maintenance of railway assets and continuous improvement of components/maintenance schedules
- Operational reliability increase (less service disruption)

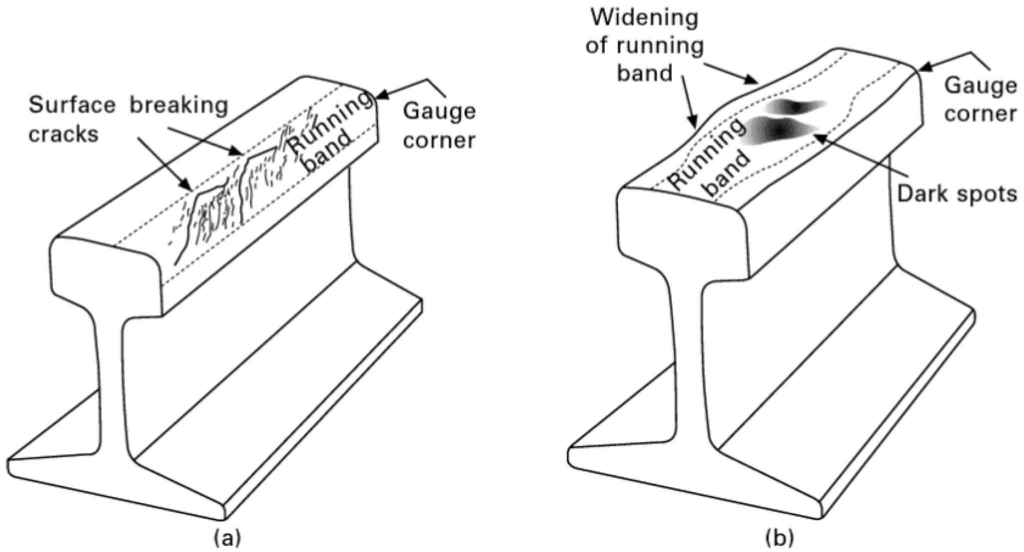
➢ Using vehicle-borne sensor data for fast and seamless infrastructure monitoring (use of in-service vehicles where possible)

➢ Automatic anomaly detection and diagnosis algorithms to allow discovery of issues in a faster way

Rail Surface Defects

- Head checks
  - Initially small and fine cracks
  - Grow down into the rail
- Squats:
  - horizontal crack below the rail surface
  - produce surface depression and widening of the running band

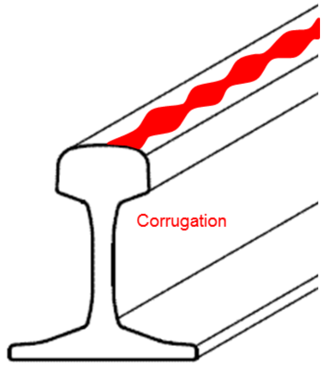
Both types of defects can lead to spalling or rail break.



Head check

Squat

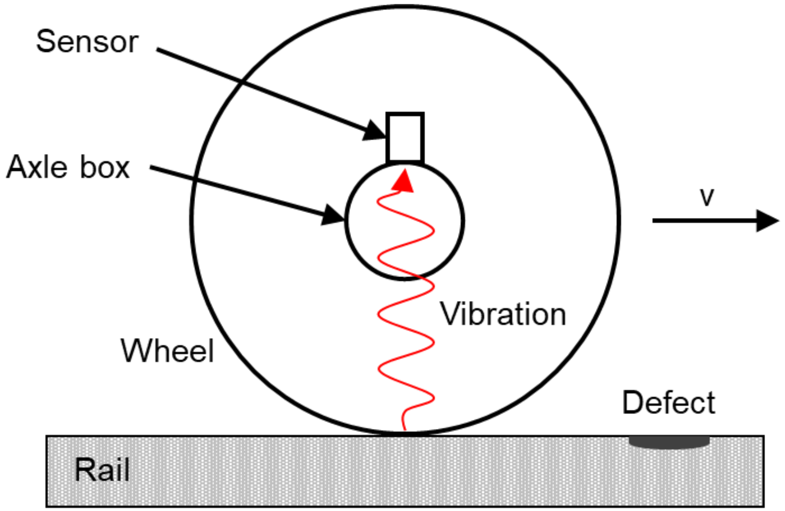
R. Lewis and U. Olofsson, Eds., *Wheel-rail interface handbook*. Boca Raton, Oxford: CRC Press; Woodhead Pub., 2009.

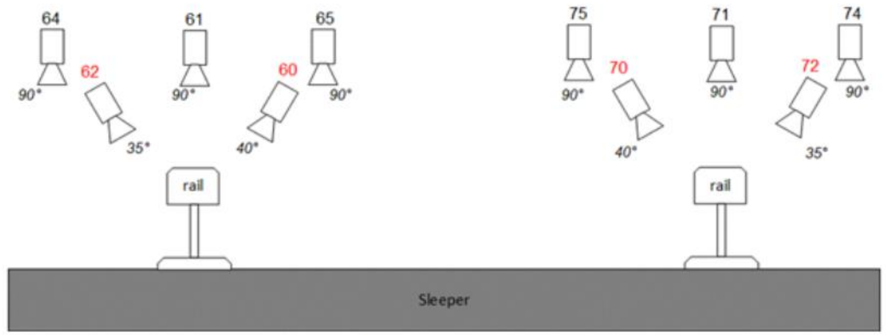


- Corrugation:
  - Quasi-periodic irregularity that appears on the running surface of rails

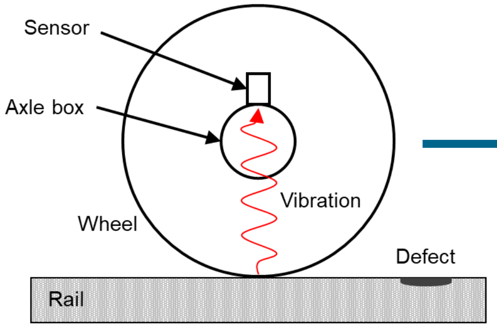
SIM - Switch Inspection & Measurement Wagon (Eurailscout)

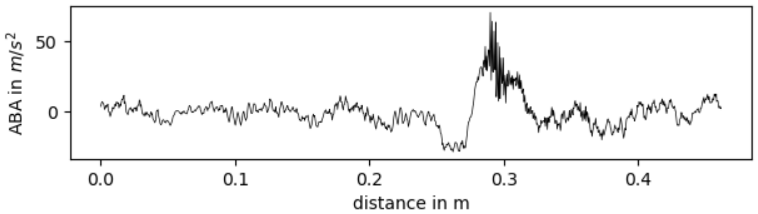
- Multiple line-scan cameras provide multi-view video stream of the rails.
- Three-component (x, y, z) axle box accelerometers (ABA) on each side of the axle measure the dynamic vehicle-track interaction.





Multi-Sensor Classification Approach



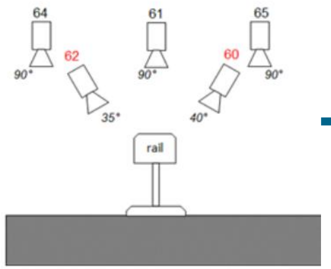


CNN Classifier

Defects
Yes
No

CNN Classifier

Severity
Mild
Medium
High



CNN Classifier

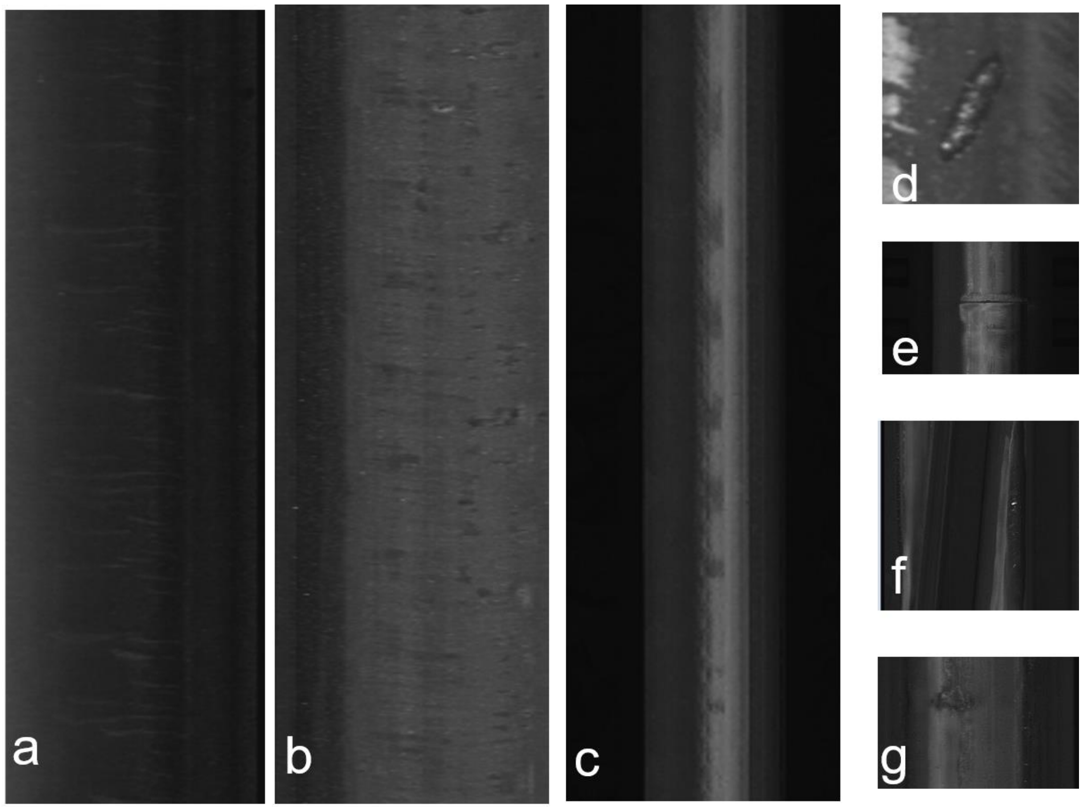
Corrugation
Yes
No

CNN Classifier

Squats
Yes
No

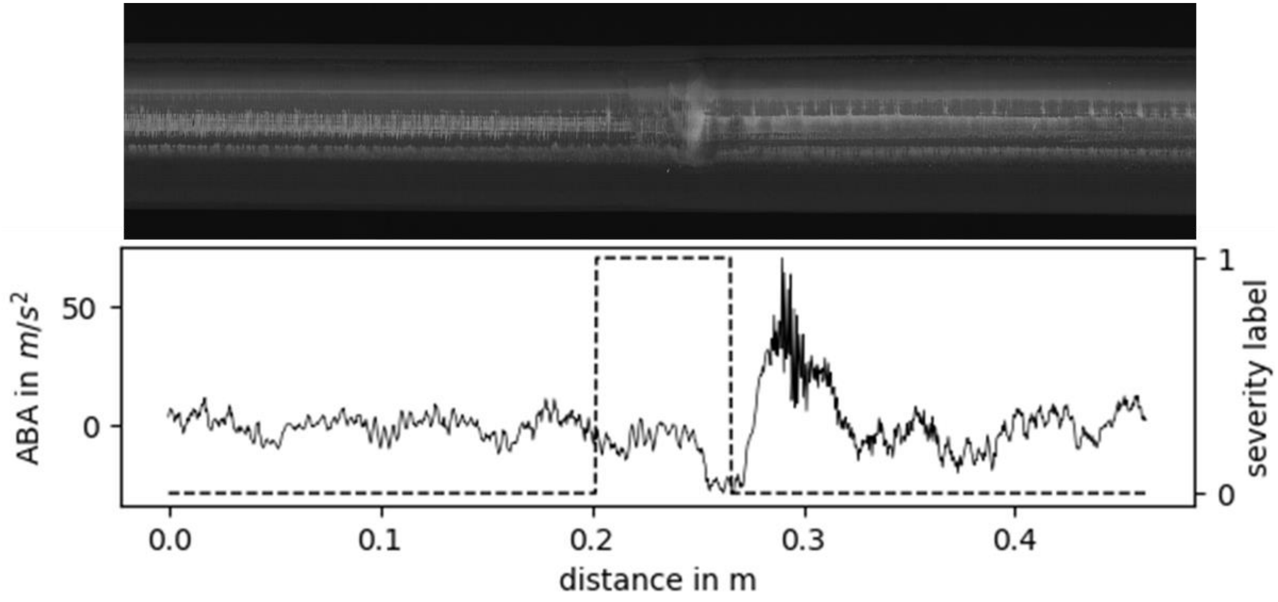
Annotated Rail Surface Defects

a) Head check
b) Stud
c) Corrugation
d) Others
e) Heavy Squat
f) Medium Squat
g) Mild Squat



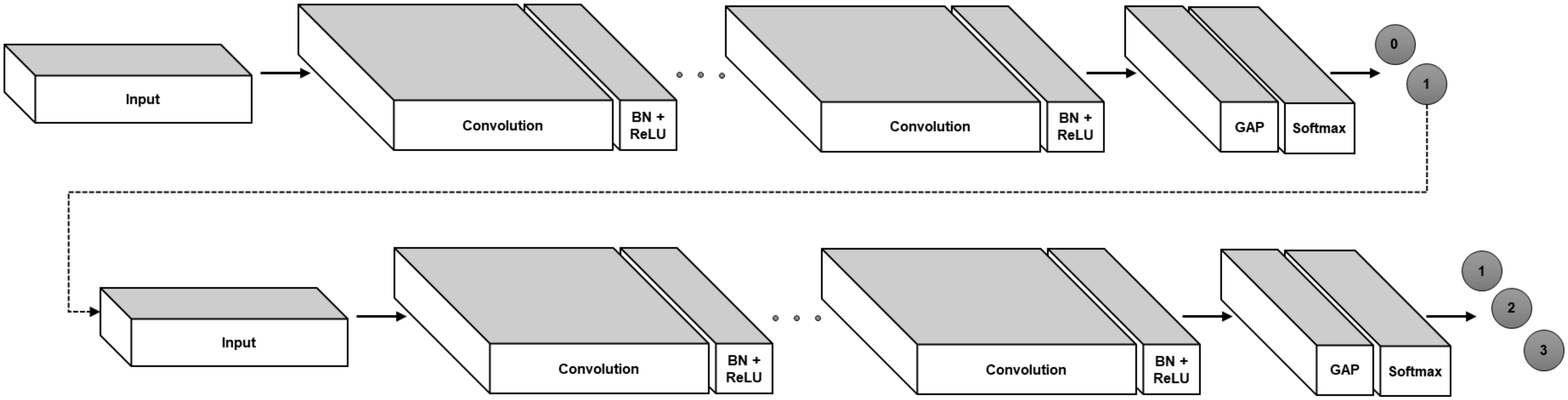
ABA Classifier

- Goal: Classification of defects' severity level [intact, low, medium, high]
- Pre-processing:
  - Time series is divided in windows of 1,000 samples.
  - Labels are extracted from image bounding boxes and assigned to each of the windows.
  - Data that contain welds and joints are excluded.



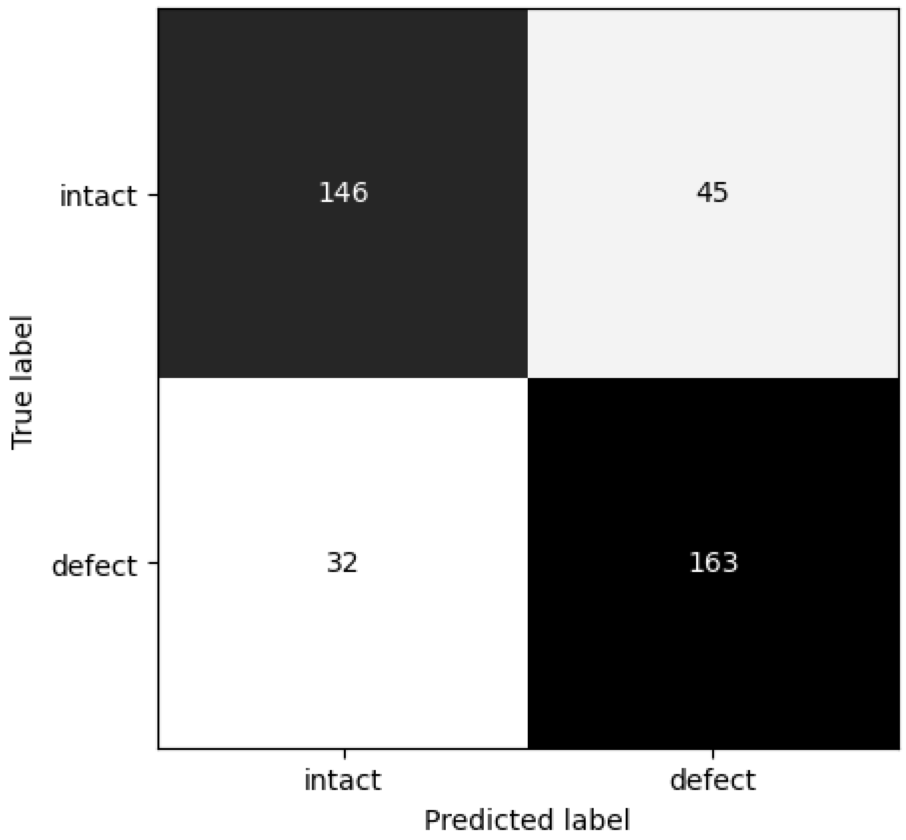
Fully convolutional network for ABA based detection and severity classification

- Two (or more) consecutive Networks
  1. Binary classification for defect detection
  2. Severity level classification of detected defects



ABA Classifier - Defect Detection Results

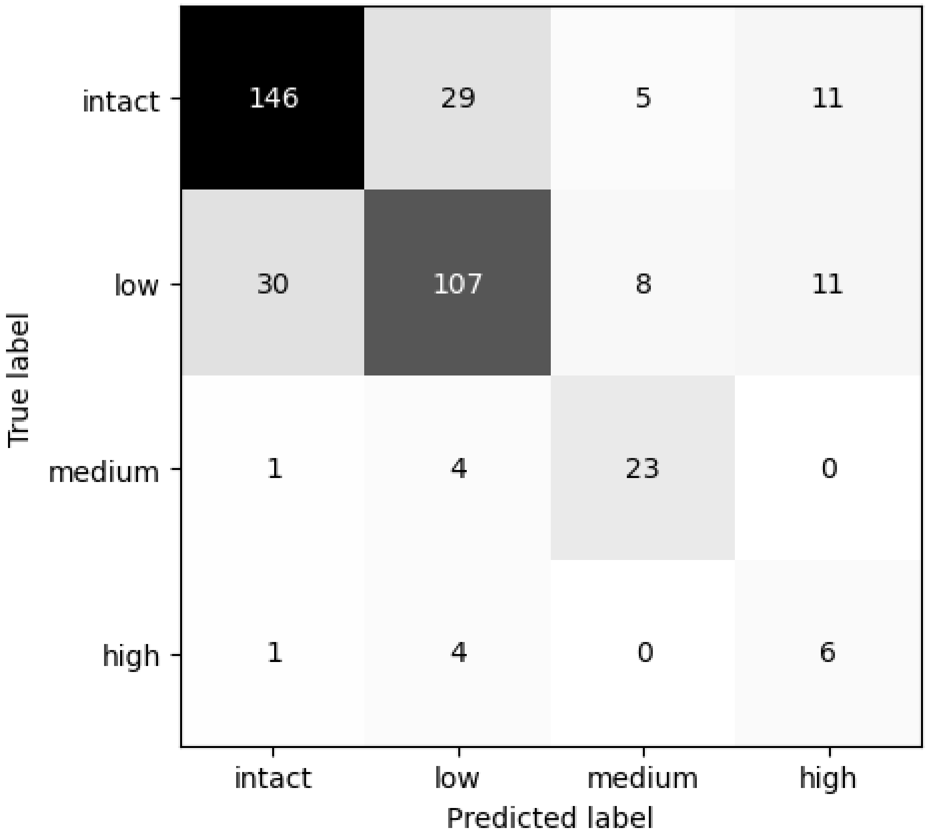
Score	Intact	Defect
Recall TP/(TP+FN)	76 %	84 %
Precision TP/(TP+FP)	82 %	78 %
FDR FP/(FP+TP)	18 %	22 %
F1-Score 2TP/(2TP+FP+FN)	79 %	81 %



- 84 % of labelled defects detected
- 18 % of the detected defects are false alarms

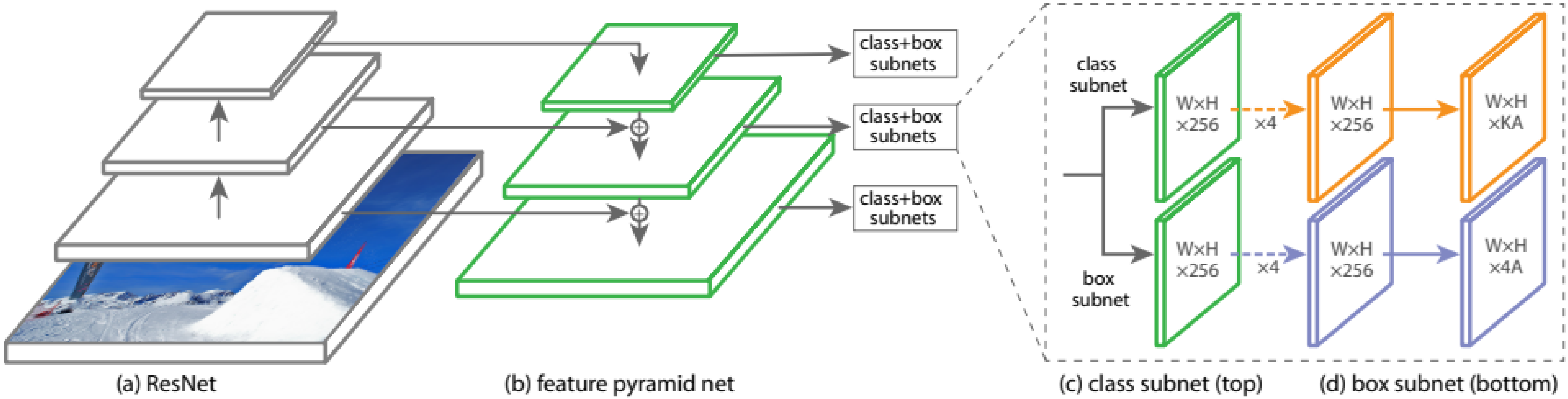
ABA Classifier - Severity Level Results

Score	Intact	Low	Medium	High
Recall TP/(TP+FN)	76 %	69 %	82 %	55 %
Precision TP/(TP+FP)	82 %	74 %	64 %	21 %
FDR FP/(FP+TP)	18 %	26 %	36 %	79 %
F1-Score 2TP/(2TP +FP+FN)	79 %	71 %	72 %	31 %



- 82 % detected defects are classified correctly in terms of severity level

Architecture of RetinaNet

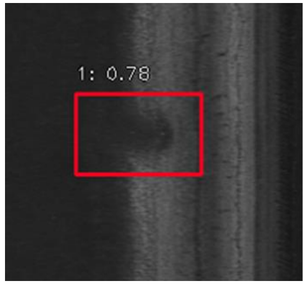


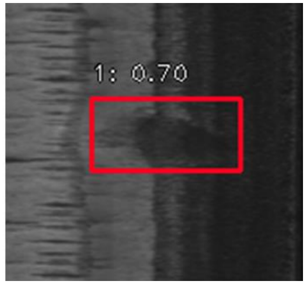
- ResNet-50 as bottom-up pathway
- Feature Pyramid Network used for top-down pathway
- Transfer Learning → Weights pretrained on COCO data set

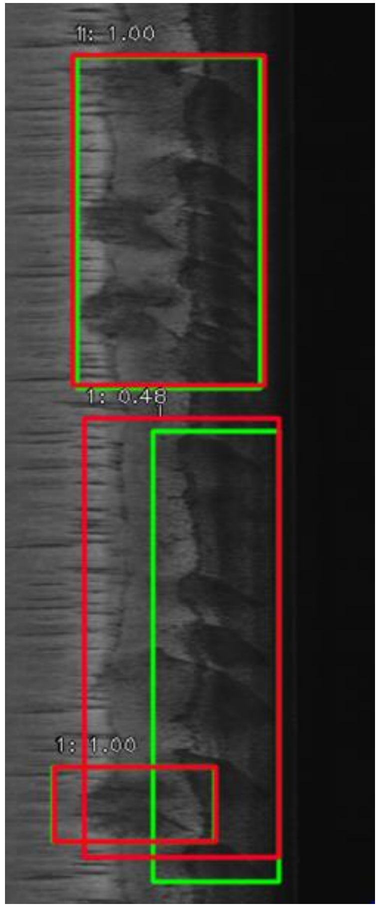
Classification Results for Squats

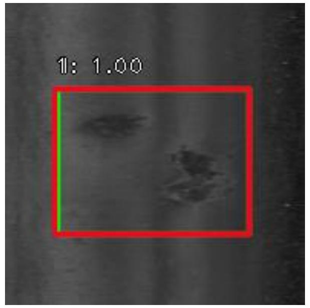
- 71 % of labelled squats detected

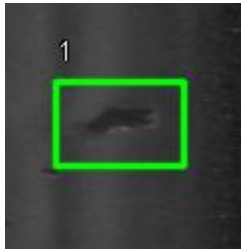
- 24 % of squat detections are false alarms
- Some false alarms indicate miss-labelled true defects.





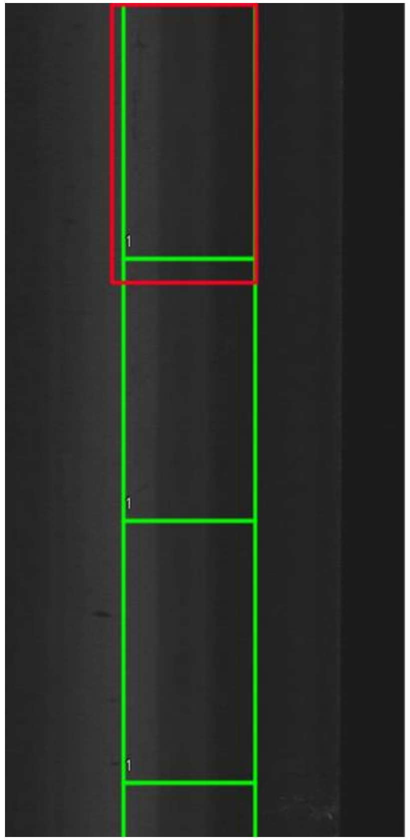


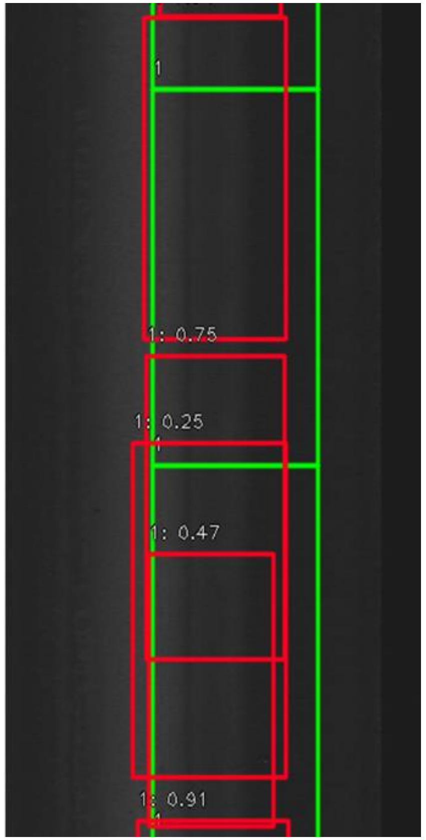




Classification Results for Corrugation

- The width-to-height ratio of all the labels is brought to 1:2 for the image classifier.
- 67 % of labelled corrugation detected
- High number of missed corrugation is related to subdivision of instances into multiple labels
- No false alarms encountered





Summary

- Independent CNN-based classifiers for image and ABA data have been trained and tested on manually labelled data.
- Considering the small amount of labelled data, a good performance for both classifier could be achieved.
- Enhancing the available labeled data and performing iterative training of the network is expected to improve performance significantly.
- Detection of overlooked defects shows potential of using neural networks to produce sudo labels instead of only relying on manual data inspection.
- In the future, a single network fusing both data sets shall be trained and evaluated.