Industrial Pipeline Infrastructure Inspection

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Artificial Intelligence & Information Analysis Lab

Industrial Pipeline Infrastructure Inspection

- **Overview**
- Pipeline Region Segmentation
- Pipeline Damage Detection
- 3D Pipeline Damage Localization
- X-ray Pipeline Damage Detection
- PEC Pipeline Damage Detection

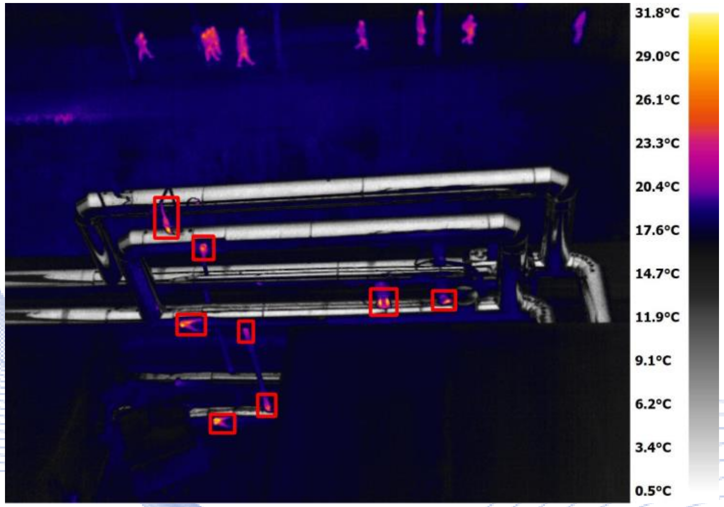
Overview

Main objective

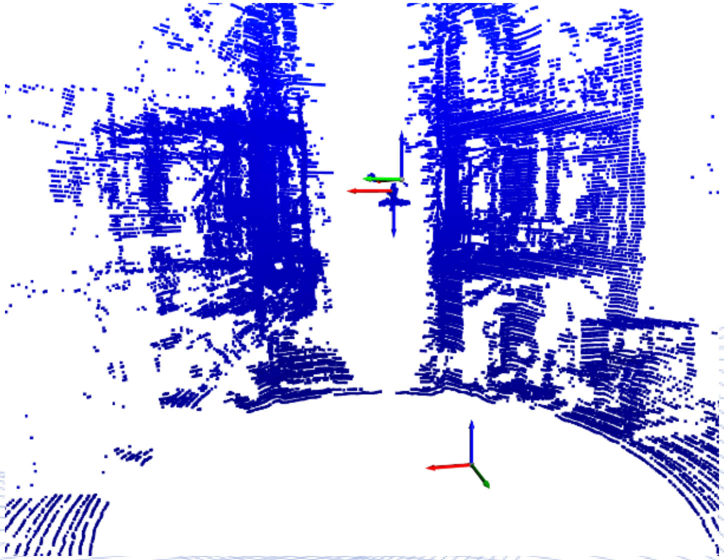
- To develop an artificial intelligence system that will analyze all the captured data by SIMAR robotic systems to reduce the inspector workload and stress.

Overview

Visual Inspection Sensors



Thermography



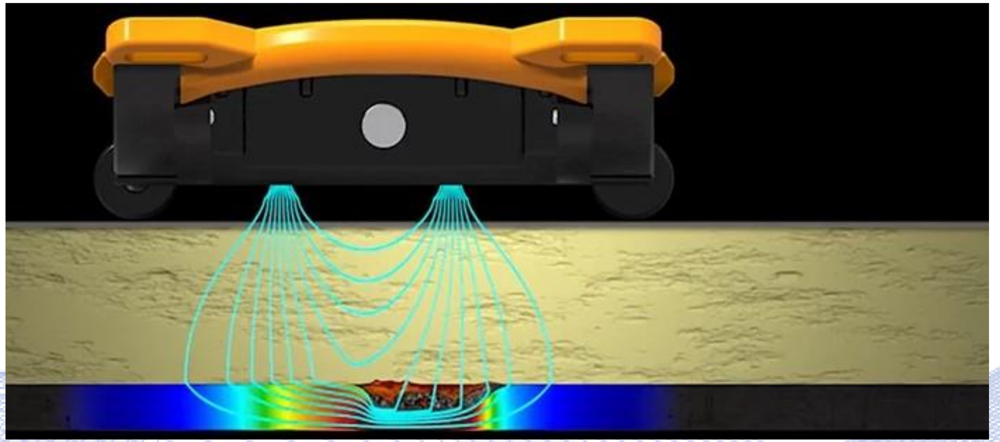
3D mapping (LIDAR)

Camera & video

Overview

Inspection Sensors for Corrosion under Insulation (CUI)

XR imaging



Pulsed Eddy Current measurements

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Overview

Functionality	Description
Insulated pipeline localization in image/video (2D) coordinate system	The system will analyze images/video and will produce annotations of the locations of the insulated pipeline
Damage localization in image/video (2D) coordinate system	The system will analyze images/video and other sensor data to produce annotations of detected damage on the insulated pipeline
Damage classification	The system will classify the detected damage to different categories
XR damage recognition	The system will analyse XR data to automate XR inspection
PEC corrosion detection	The system will analyse XR data to automate PEC inspection
3D damage localization	The system will localize the damage in a 3D coordinate system (3D map)

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Overview

- **Insulated Pipeline Region Segmentation**
  - Developed pipeline segmentation algorithm: pipeline segmentation model and a prompting module.
  - Created a pipeline segmentation dataset.
  - Extensive evaluation of the pipeline segmentation model.

- **Pipeline Damage Detection/Classification**
  - Developed damage detection/classification algorithm: Lightweight DNN (Yolo, RT-DETR) detectors and changes detection algorithm.
  - Enriched damage detection/classification dataset.
  - Extensive evaluation of the developed algorithms.

Overview

- **3D Pipeline Damage Localization**
  - Developed an algorithm for localizing in the 3D space the 2D detected bounding boxes of pipeline damages.
  - Developed the Enhanced Robust Cylinder Fitting algorithm (ERCFit) for single pipeline modelling.
  - Developed the 3D pipeline reconstruction framework for multiple pipeline modelling.

- **X-ray Pipeline Damage Detection**
  - Solved the task using the Yolov8 object detection algorithm.
  - Developed an image processing algorithm for corrosion detection.
  - Implemented modern anomaly detection algorithms for corrosion detection.

Overview

- **PEC Pipeline Damage Detection**
  - Established a corrosion level scale.
  - Developed the CLD algorithm for corrosion localization in PEC measurements.

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Pipeline Region Segmentation

- Segmentation is part of the visual inspection task performing the visual classification of the pipes (insulated pipe/background).

- The localization of the insulated pipes in the 2D plane improves the damage classification in the 2D plane by validating the detections (whether or not the detection is located on the pipe).

Functionality	Description
Insulated pipe localization in image/video (2D) coordinate system	The system will analyze images/video and will produce annotations of the locations of the insulated pipe
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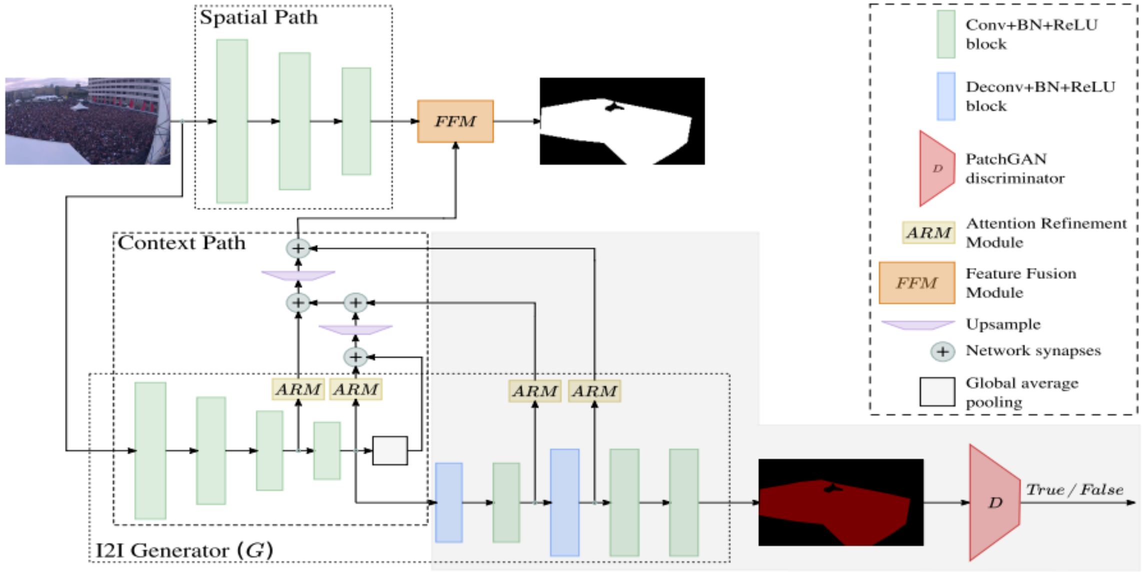
Pipeline Region Segmentation

Segmentation method [PAP2021]:

- binary semantic segmentation from single RGB images (insulated pipeline/background)
- based on Convolutional Neural Networks (CNNs)
- a semantic segmentation and an image-to-image translation (I2I) neural branch



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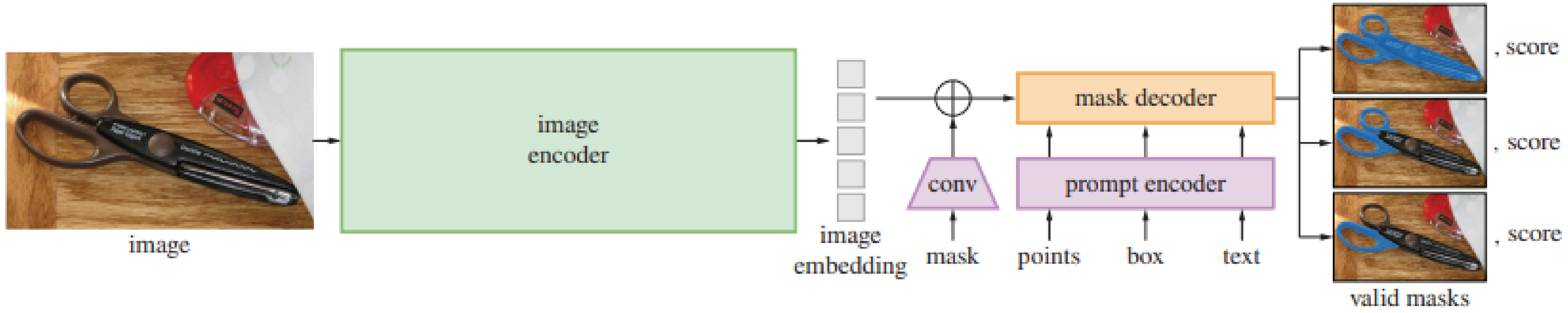
Pipeline Region Segmentation

Segment Anything Model (SAM) [KIR2023]:

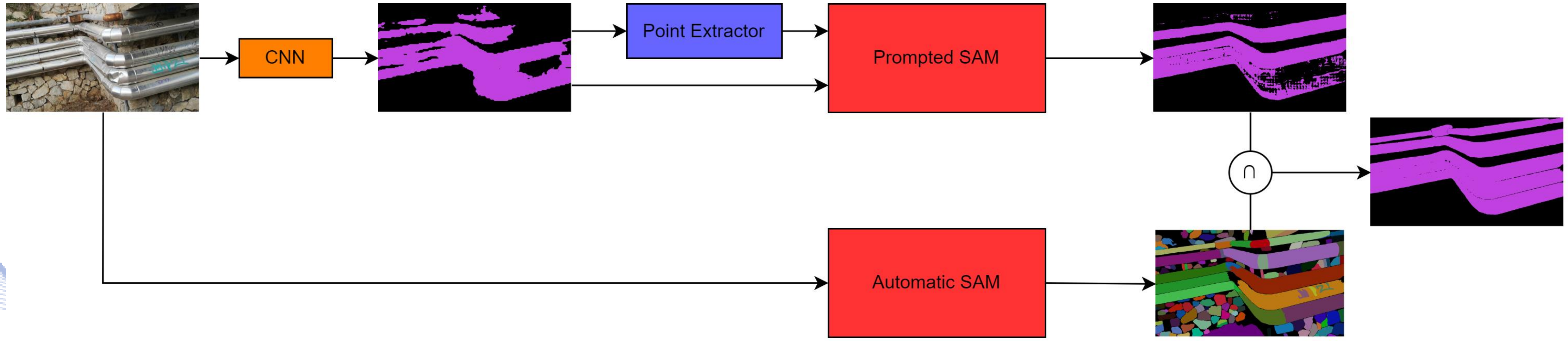
- An unsupervised model for image segmentation.
- A heavyweight image encoder produce an embedding of the input image.
- A mask decoder combines input prompts and the embeddings to produce object masks.
- Three masks are produced with associated confidence scores.



Pipeline Region Segmentation

- Cooperation of a CNN segmentation model [PAP2021] and Segment Anything Model [KIR2023].
- The CNN model produces masks of the pipelines.
- A prompted SAM goal is used to refine the segmentation masks produced by CNN model.
- SAM also runs on automatic mode to produce masks for all objects.
- The final segmentation mask is produced by fusing the two intermediate outputs.

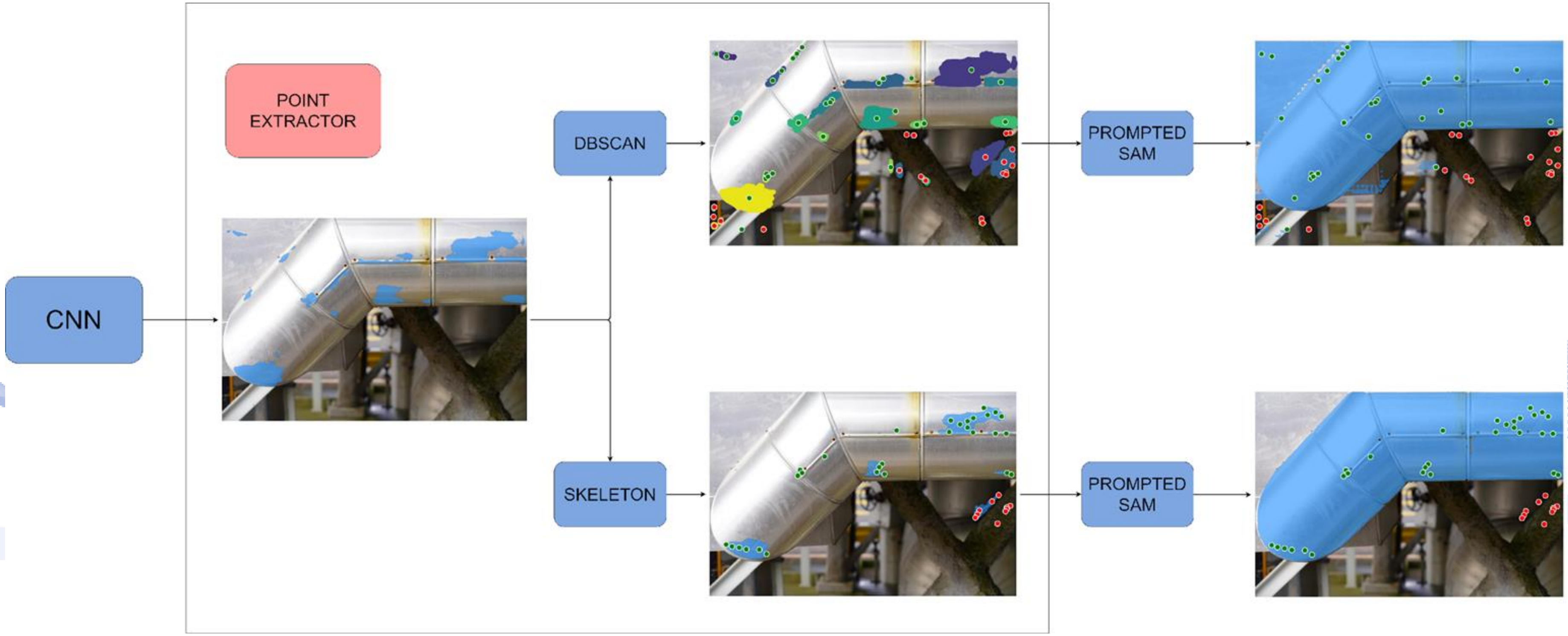
Pipeline Region Segmentation



CNN	CNN for semantic segmentation	Point Extractor	Point Extraction Module	Prompted SAM	Prompted SAM model	Automatic SAM	Automatic mask generation SAM	∩	Mask Matching

Pipeline Region Segmentation

Enhancement of the Point Extractor module by replacing the DBSCAN algorithm with a new method for extracting pipe representative points.



Comparison of point extractor modules.

Pipeline Region Segmentation

- DBSCAN was used in initially in the Pipe segmentation model.
- DBSACN: fastest of the clustering methods, arbitrary number of clusters.

CNN prediction with confidence over 99%.

DBSCAN clustering on the predicted masks.

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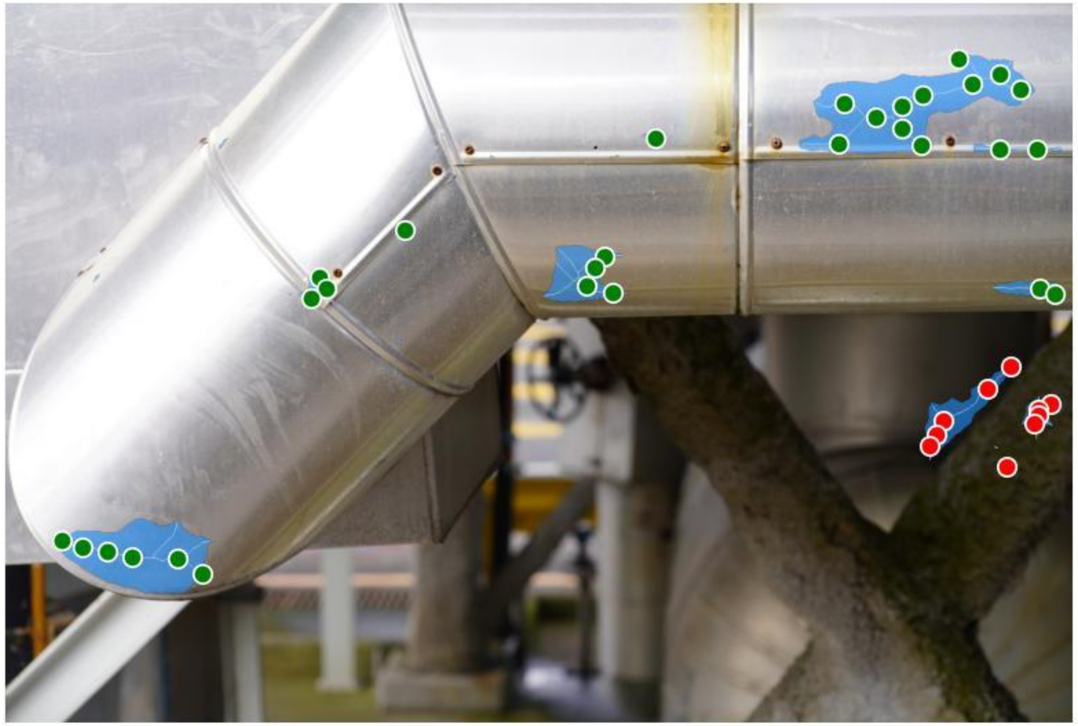
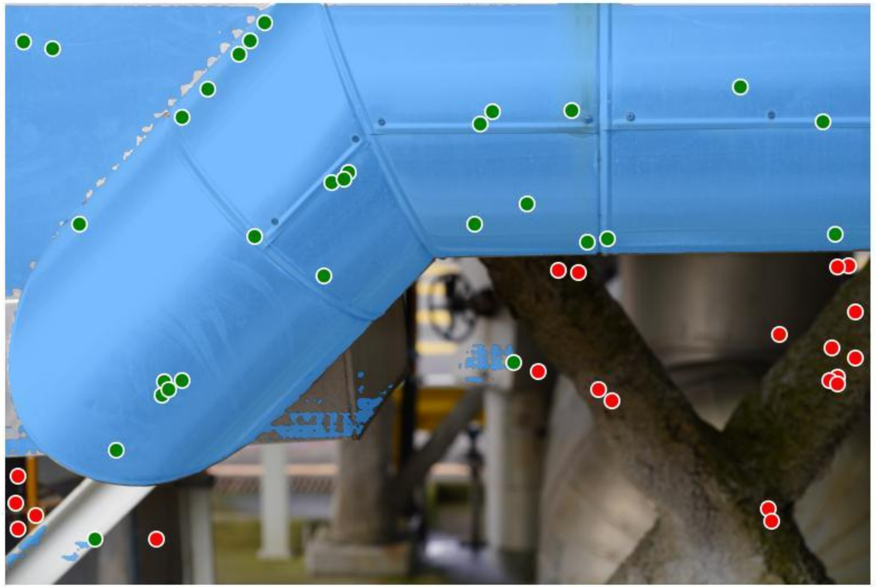
Pipeline Region Segmentation

- Erosion: morphological operation to eliminate small areas.
- Skeletonization: create a connected medial graph along the limbs of the mask areas.
- Sample uniformly the skeletons to create a list of prompts.

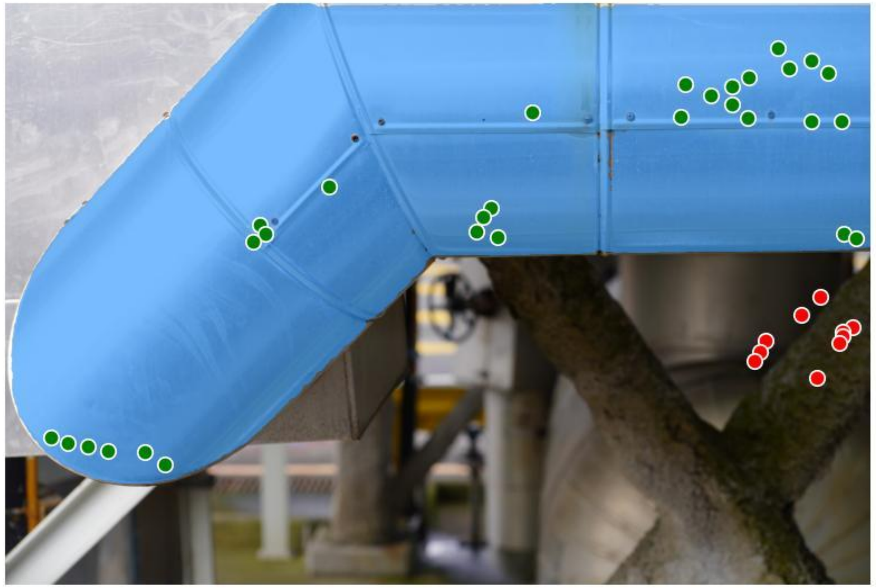


Pipeline Region Segmentation

- New point extractor: removes small areas of false positives in the CNN prediction and sample more point per area.
- New point extractor runs 4 times faster than DBSCAN.



Prompted SAM prediction using the points extracted from DBSCAN.



Prompted SAM prediction using the points extracted from the new point extractor.

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Pipeline Region Segmentation

- Erosion: morphological operation to eliminate small areas.
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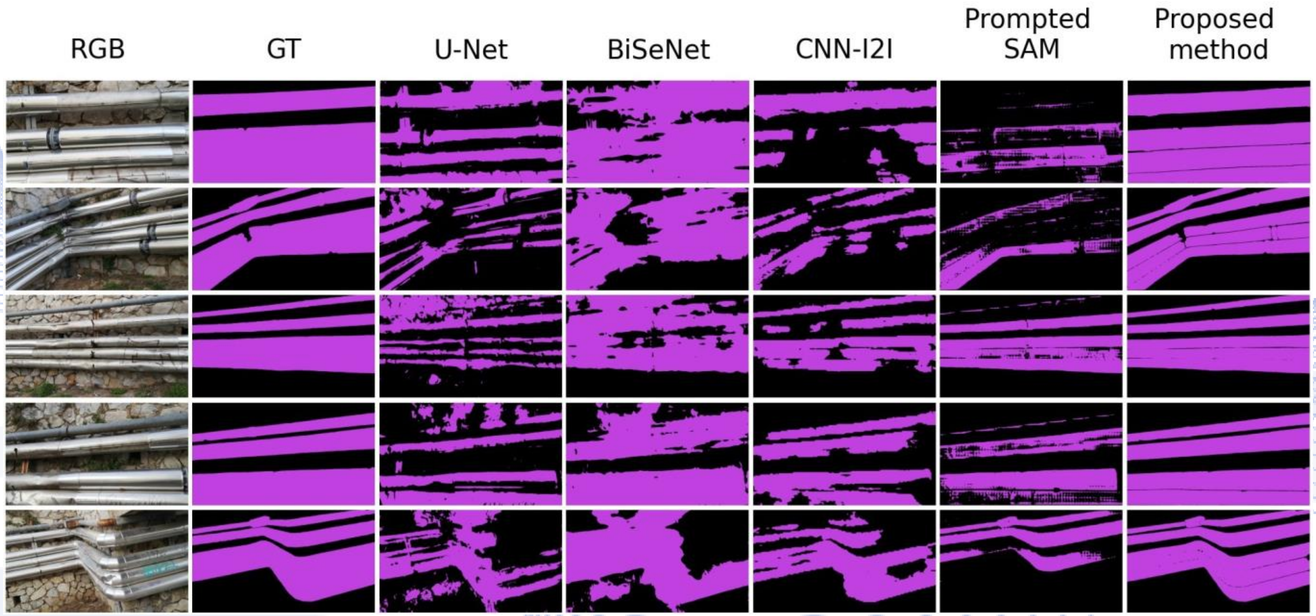
Pipeline Region Segmentation

- Training dataset: ~1000 annotated RGB images collected from a typical European refinery premises (901), Greek refineries and hospitals (78)
- Validation dataset: 77 annotated RGB images collected from the AUTH site
- Test Dataset: 195 RGB images collected from a typical European refinery using a UAV.

Validation dataset (AUTH site)

Pipeline Region Segmentation

- The performance of the model was evaluated using the Intersection-over-Union (IoU) metric.



	IoU (%)			
	non-pipe	**pipe**	**mIoU**	**mPA(%)**
U-Net [7]	52.0	46.1	49.0	66.0
BiSeNet [8]	54.2	65.4	59.8	75.4
I2I-CNN [9]	68.5	63.7	66.1	79.7
prompted SAM	78.9	79.3	79.1	88.3
Proposed System	**89.0**	**90.9**	**89.9**	**94.8**

D. Psarras, C. Papaioannidis, V. Mygdalis, and I. Pitas, “A Unified DNN-Based System for Industrial pipeline Segmentation”, submitted as conference paper.

Pipeline Region Segmentation

Training dataset	Model	IoU (%) non-pipe	IoU (%) pipe	mIoU (%)	mPA (%)
Validation dataset	I2I-CNN	83.9	85.3	84.6	91.7
	SIMAR segmentation model	90.2	91.4	90.8	95.8
Test dataset	I2I-CNN	83.9	72.8	78.3	88.8
	SIMAR segmentation model	90.2	81.7	85.9	93.2

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Pipeline Damage Detection

- **Detection/classification:**
  - YOLO-based algorithm [CHU2022] :
    - Extract features from CNN-based backbone.
    - Integrate features at multiple scales.
  - RT-Detr-based algorithm [WEN2023] :
    - Transformer based detector.
- **Changes detection:**
  - Deep autoencoder model:
    - Learns the distribution of non-damaged pipelines.
    - Detects the images/patches that differ from learned distribution (and possibly contain damaged pipelines).

Pipeline Damage Detection

Pipeline damage in a Greek factory.

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Pipeline Damage Detection

Performance of damage detection/classification algorithms

Model	Dataset	Mean Average Precision	Mean Average Recall
YOLO-NAS	D2023-07-01	0.39	0.776
YOLOv6L6	D2023-07-01	0.519	0.705
YOLOv6L6+SAHI	D2023-07-01	0.521	0.730
Rt-Detr	D2023-07-01	0.472	0.77
Rt-Detr+SAHI	D2023-07-01	0.45	0.54
YOLOv6L6	D2023-09-30	0.52	0.78
Rt-Detr	D2023-09-30	0.45	0.77
Rt-Detr+YOLOv6-Backbone	D2023-09-30	0.40	0.65
YOLOv6L6	**D2023-10-20**	**0.52**	**0.82**
Rt-Detr	D2023-10-20	0.46	0.78

Performance of changes detection algorithms

Methods	Precision	Recall
Autoencoders	0.55	0.91
Autoencoders with one-class SVM	0.56	0.89
ResNet-50 with Local Outlier Factor	0.36	0.86

Pipeline Damage Detection

Slicing Aided Hyper Inference (SAHI) [AKY 2022]

- Object detection forward pass is applied independently to l number of $M \times N$ overlapping patches.
- Results are merged back into original size using NMS (Non Maximum Suppression).

Pipeline Damage Detection

- Damage detection/classification:
  - Develop algorithm for rotated object detection to enclose damages more accurately.
  - Combine object detection models with object tracker to further improve damage detection performance for video inputs.
- Changes detection:
  - Improve model by focusing on image patches instead of the whole image.
  - Develop algorithm to localize anomalies or damages.

Pipeline Damage Detection

Overall pipeline damage detection and visualization.

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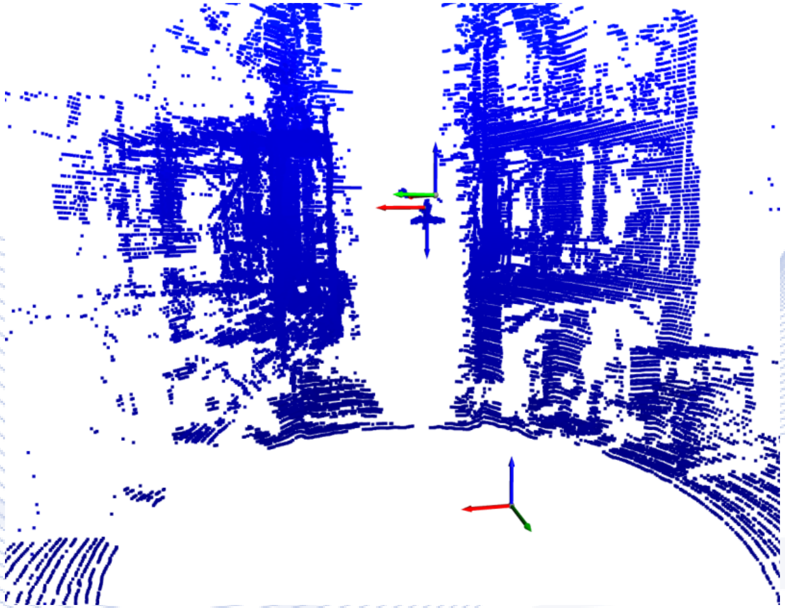
3D Pipeline Damage Localization

Developed algorithm for 3D pipe defect localization.

- **Input**: Point cloud, position & orientation of coordinate systems, 2D bounding boxes of the damages on the image.
- Apply transformation for camera and LiDAR coordinate systems to properly position this coordinate systems within the “map” coordinate system.
- Project the frustum of the image alongside the 2D bounding boxes to accurately localize damages.



Input Point Cloud

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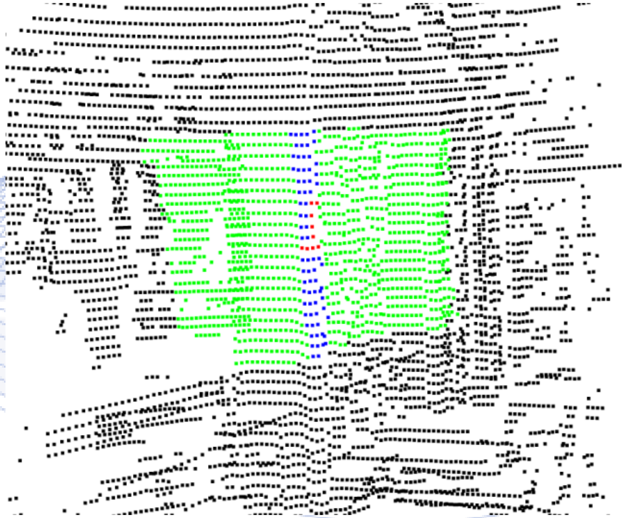
3D Pipeline Damage Localization

Result of the 3D damage localization algorithm.

- Green: The points corresponding to the image.
- Blue: The points enclosed by the blue bounding box of the pipeline.
- Red: The points enclosed by the two red bounding boxes of damages.

2D Damage Detection



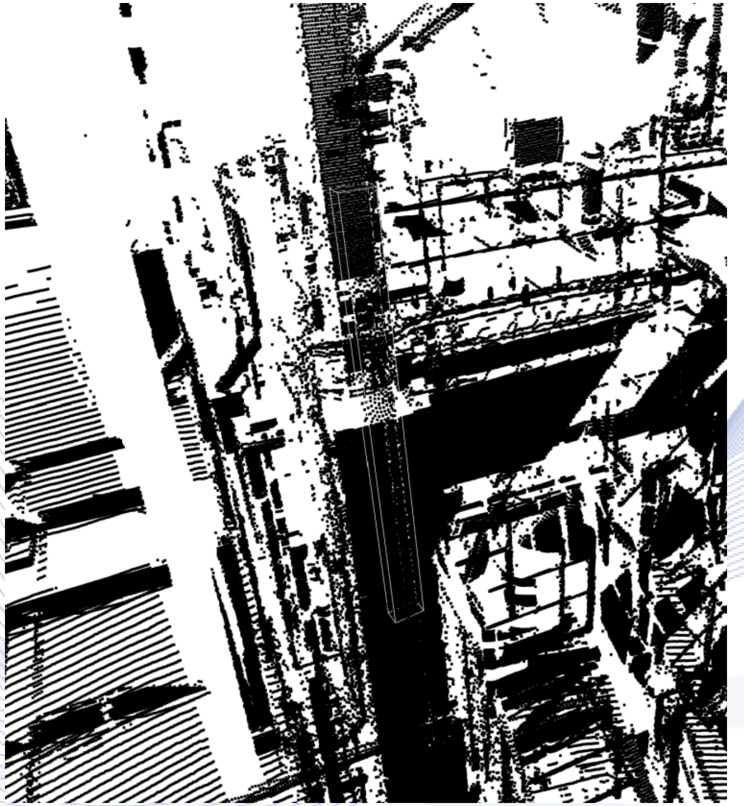
3D Damage Localization

3D Pipeline Damage Localization

3D Damage Localization Output

The output is an oriented 3D bounding box, defined by the following parameters:

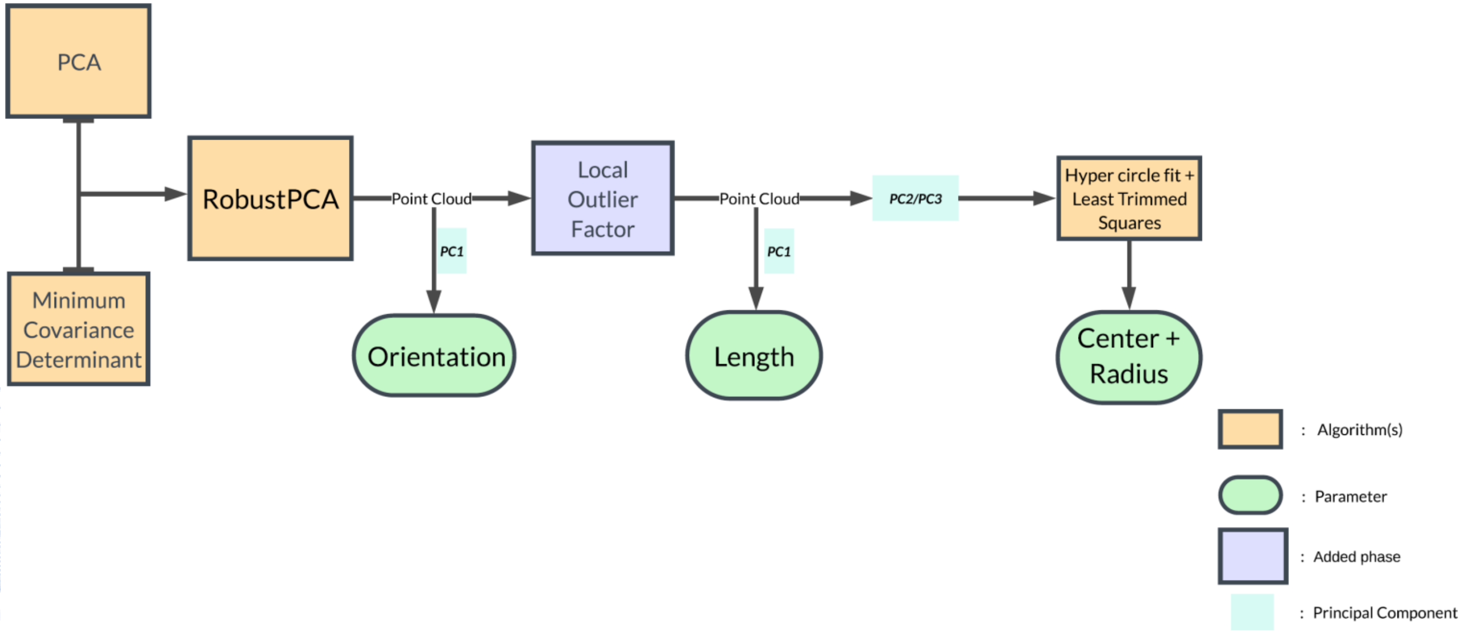
- **Center Coordinates (X, Y, Z):** Representing the center point of the 3D bounding box.
- **Dimensions (Width, Height, Depth):** Specifying the size of the bounding box.
- **Rotation Matrix (3x3):** Describing the orientation of the 3D bounding box.



3D Bounding Box for Damage Localization

3D Pipeline Modelling

Enhanced Robust Cylinder Fitting algorithm (ERCFit) for single pipeline modelling

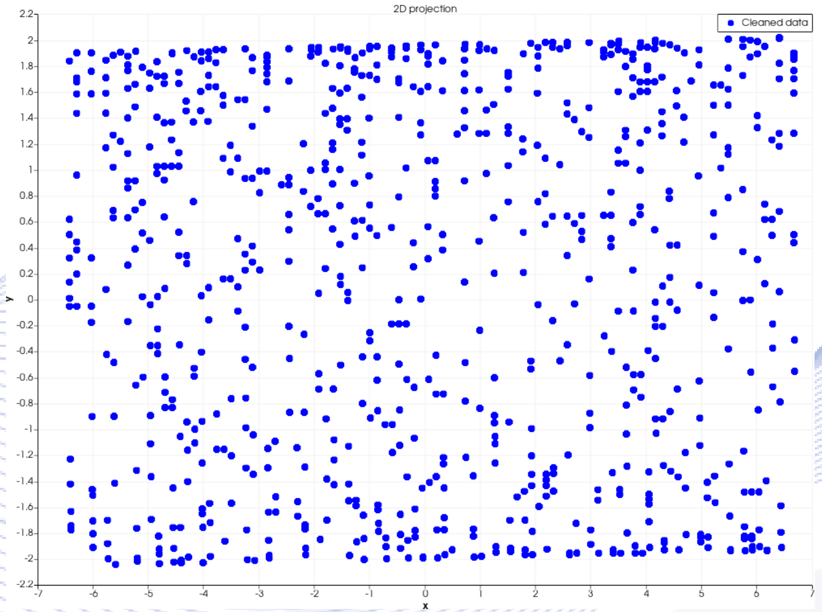


ERCFit workflow: PCA, MCD, LOF, and Hyper Fit algorithm for cylinder fitting

3D Pipeline Modelling

- Orientation is calculated using the Principal Component Analysis 1 (PCA1)
- The length of the cylinder is computed as:

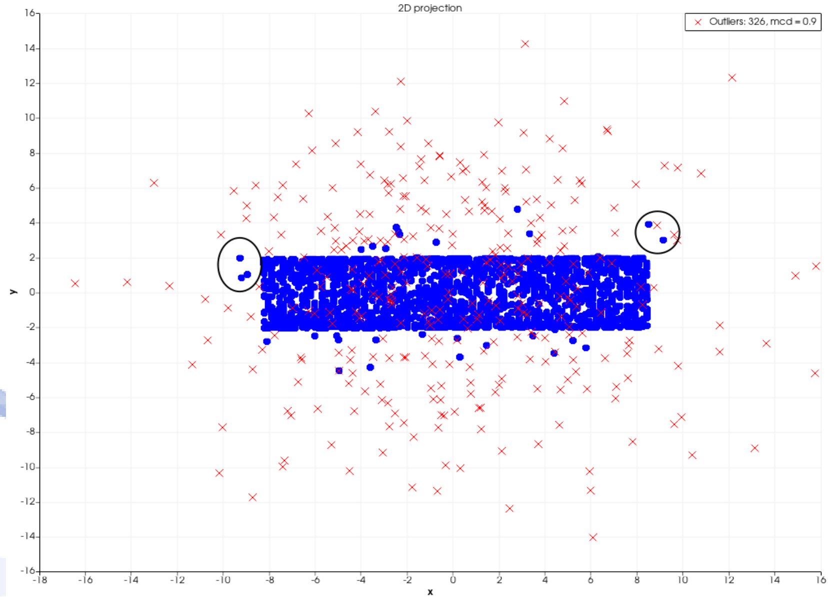
$$L_c = \max_{p \in P}(p \cdot pc1) - \min_{p \in P}(p \cdot pc1)$$



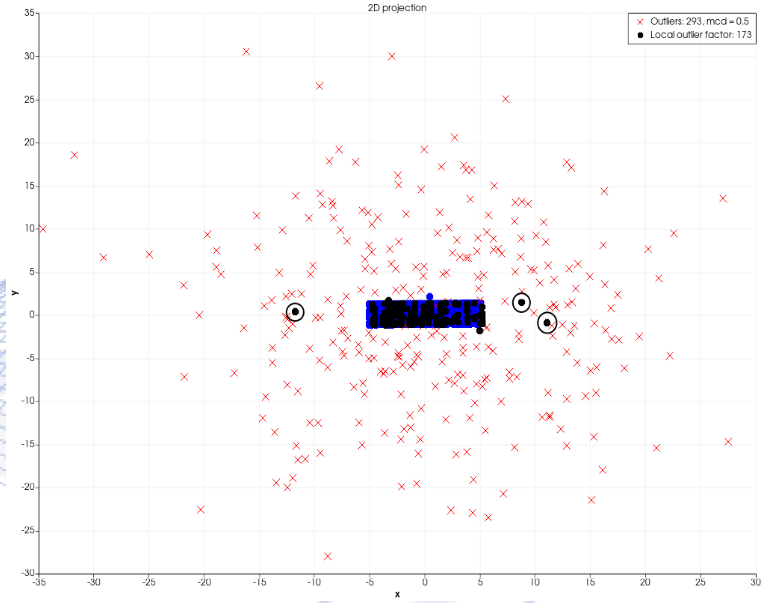
Point cloud projection onto PCA1 and PCA2

3D Pipeline Modelling

The Minimum Covariance determinant (MCD) and the Local Outlier Factor (LOF) are used to remove outliers, improving the accuracy in cylinder length and centre calculations.



Minimum Covariance determinant (MCD) with missed outliers



Local Outlier Factor (LOF) removing outlier missed by MCD

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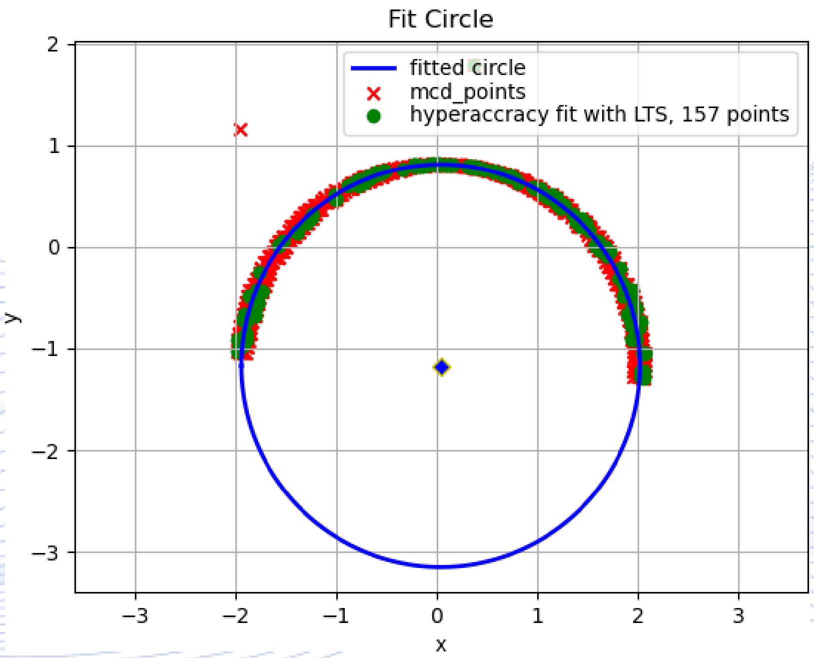
3D Pipeline Modelling

The Hyper Accuracy algorithm and the Least Trimmed Squares are used to fit a circle the point cloud.



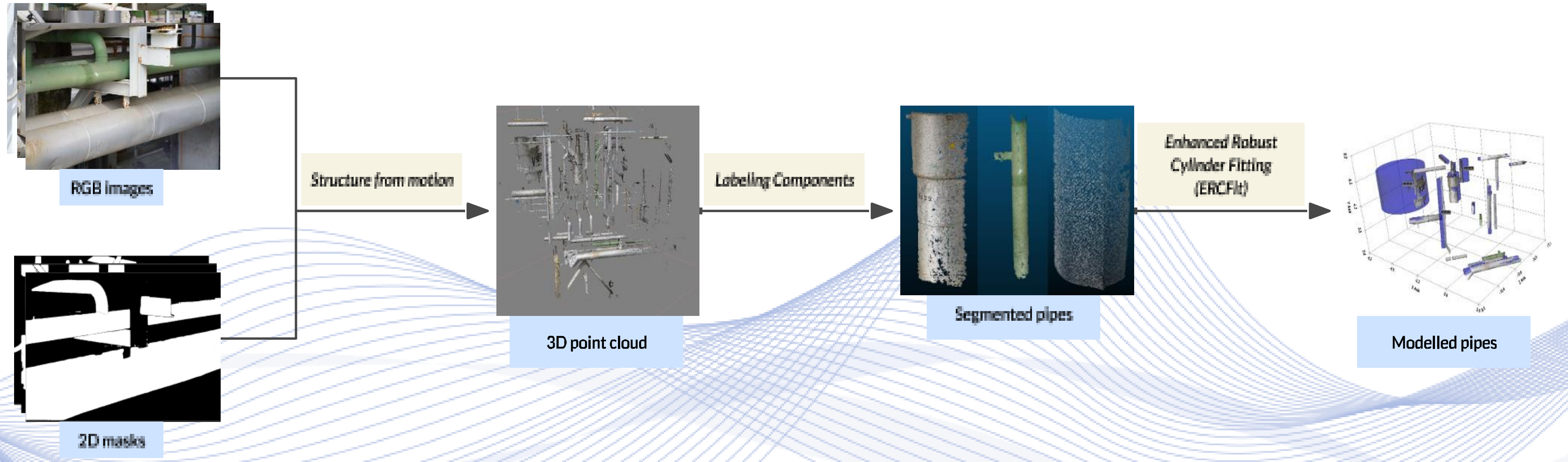
3D Pipeline Modelling

LOF algorithm significantly reduces RMSE for centre and length parameters.

Parameter	Robust Cylinder Fit	ERCFit	Gain (%)
Radius(m)	0.007	0.007	0%
Center(m)	0.254	0.21	17.32%
Length(m)	2.313	0.141	93.90%
Orientation(deg)	0.646	0.646	0%

3D Pipeline Modelling

3D pipeline reconstruction framework for multiple pipeline modelling.



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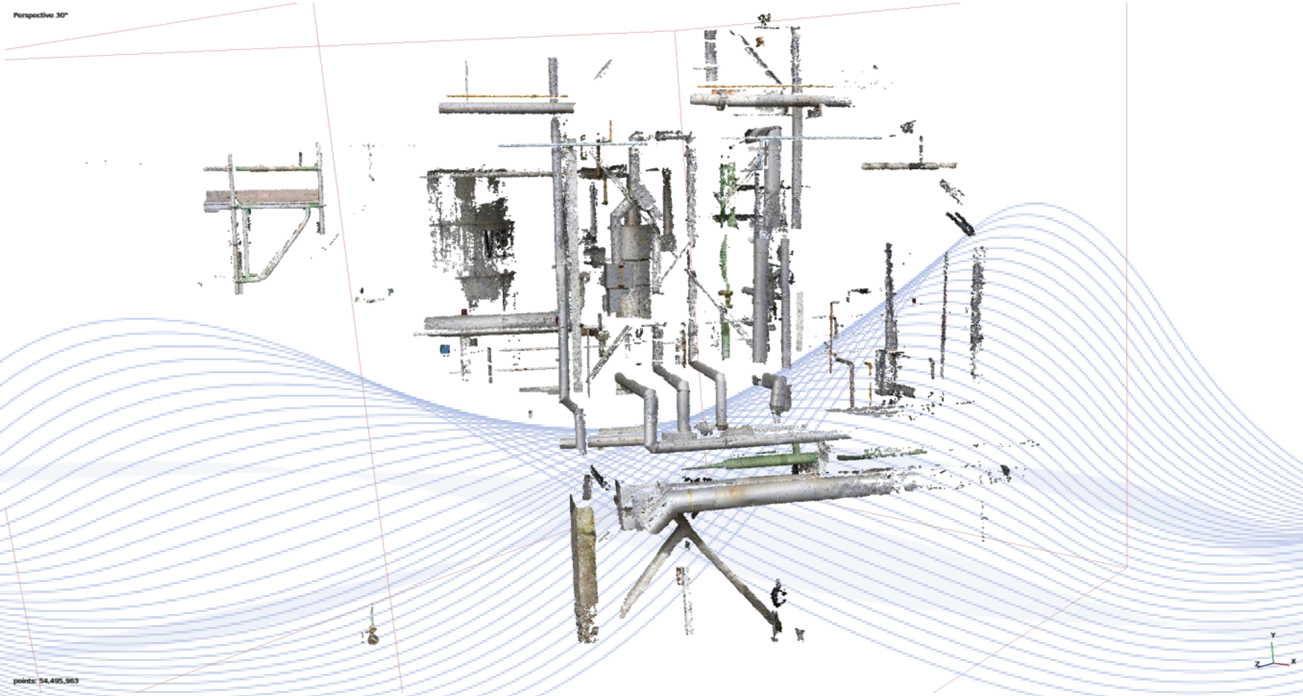
3D Pipeline Modelling

Input: 3D point cloud.



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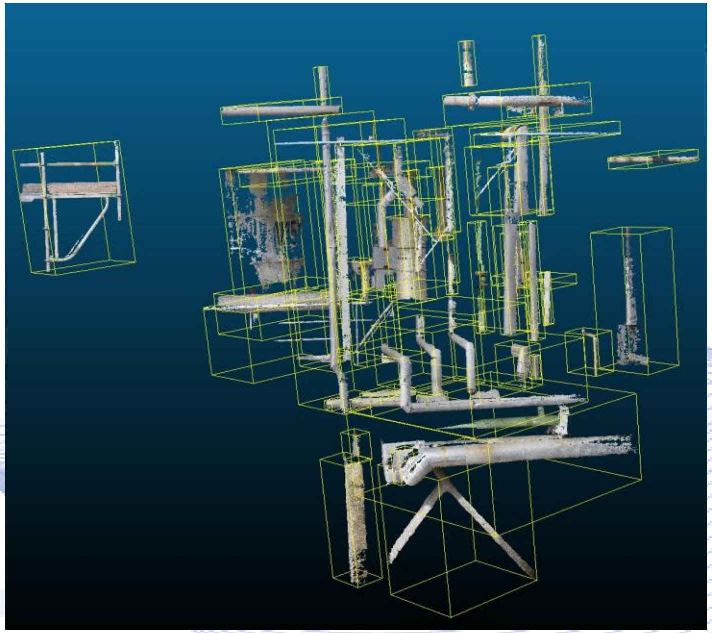
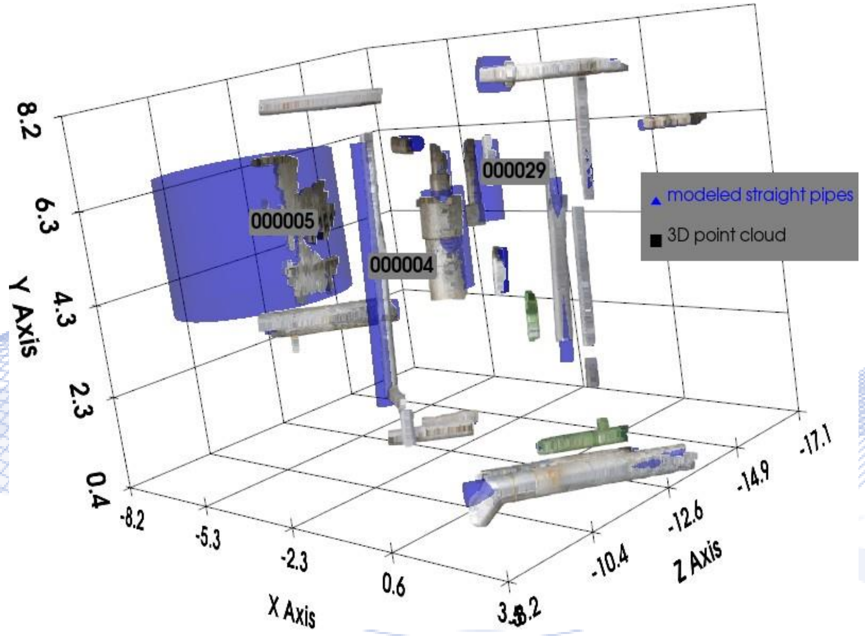
3D Pipeline Modelling

The 3D pipeline reconstruction framework first applies the Labelling Components algorithm to isolate the segmented pipelines and then models each pipeline using the ERCFit algorithm.



Segmented parts using Labelling Components algorithm



3D point cloud with reconstructed pipelines.

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X-Ray Pipeline Damage Detection

- Regarding X-rays, we have three types of datasets.
  - D_{XR1}: The X-rays are powerful, and able to penetrate the metal pipelines [YAN2021]. (This dataset was captured at the manufacturing stage)
  - D_{XR2}: The X-rays are only able to penetrate the insulation. This is the type of dataset that we deal with in the SIMAR project.
  - $D_{syntethic}$: The X-ray data have been synthetically created to look similar to D_{XR2}.

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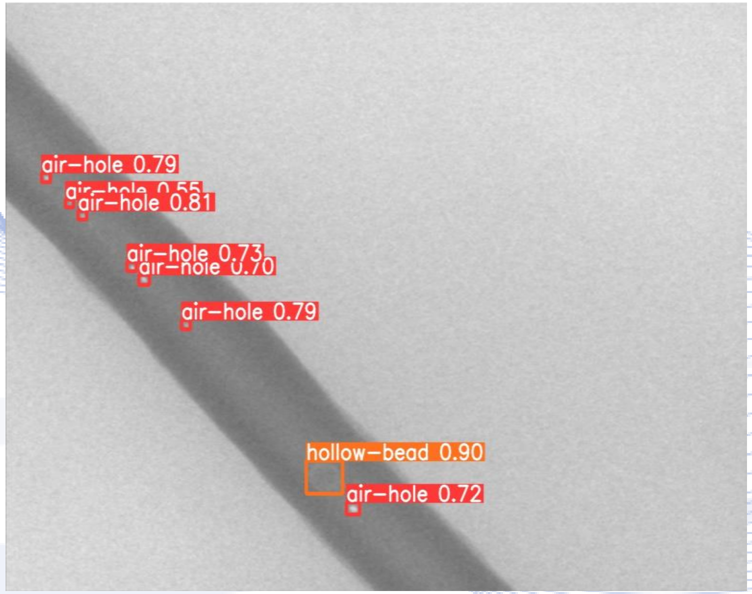
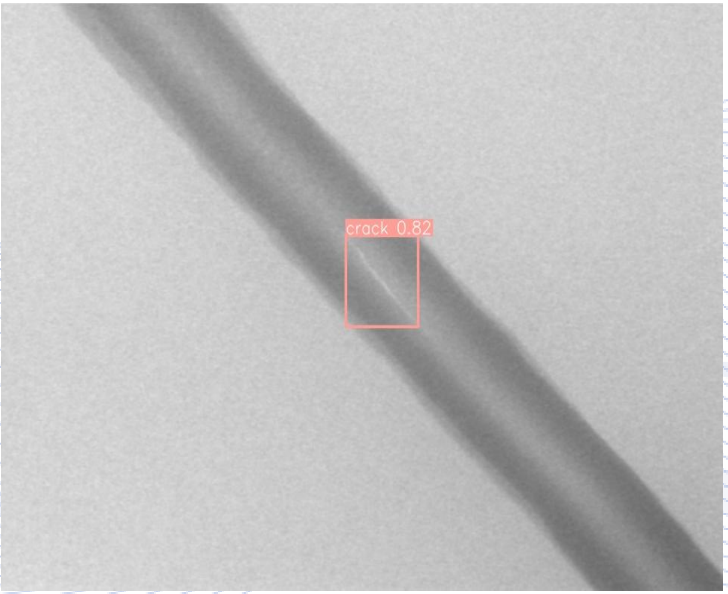
X-Ray Pipeline Damage Detection

- Trained baseline models based on YOLO object detector [CHU2022].





YOLOv8 Results	
Precision	0.97
Recall	0.96
mAP50	**0.98**
mAP50-95	0.71

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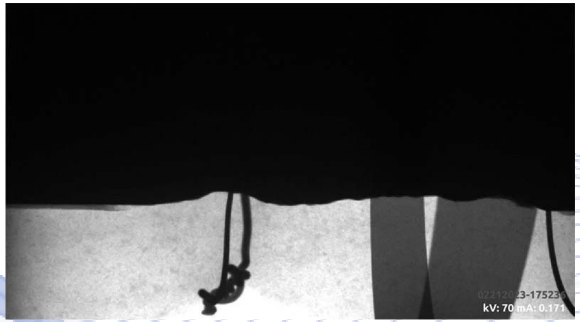
X-Ray Pipeline Damage Detection

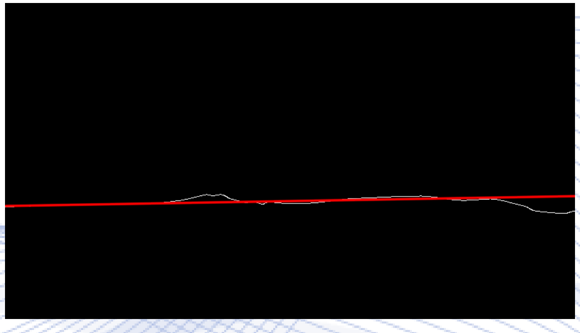
Developed a methodology based on traditional computer vision and image processing to detect corrosion.

- Passed a median and a Gaussian filter to deal with insulation noise.
- Performed Binary thresholding on the image.
- Made use of the well-established Canny edge detector.
- Performed Hough Line Transform to find a suitable line that represents the ideal pipeline edge (i.e., if there was no corrosion).

X-Ray Pipeline Damage Detection

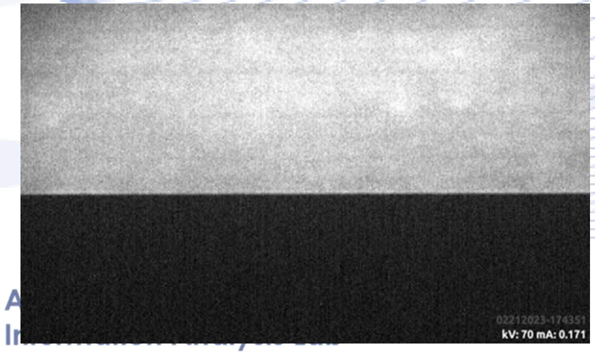
- Employ image processing techniques to detect the edge of the pipeline.
- Detect corrosion by measuring the distance from the corresponding straight line that simulates a pipeline without corrosion.

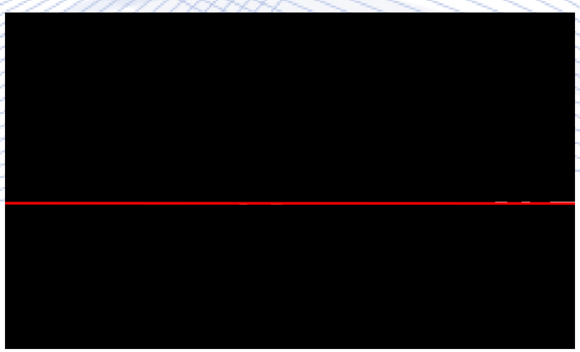




Corrosion

Images taken from [QSA]





No Corrosion

X-Ray Pipeline Damage Detection

- Several algorithms were implemented to solve the problem as an anomaly detection (AD) and anomaly localization (AL) task.
- The algorithm with the best performance is Patchcore.
- The results are near-perfect for some algorithms, because of the simplicity of the task for modern AD/AL algorithms, as well as the low variance of dataset X-ray images.

Algorithm	*Precision*	*Recall*	*F1 Score*	*Accuracy*	*AUC*
CFA	0.788	0.850	0.818	0.790	0.849
Cflow	0.889	0.932	0.910	0.898	0.960
DFM	0.988	**0.996**	0.992	0.991	**1.000**
FastFlow	**0.996**	0.994	0.995	0.994	0.999
GANomaly	0.561	0.990	0.716	0.563	0.672
PaDiM	0.810	0.944	0.872	0.845	0.913
Patchcore	**0.996**	**0.996**	**0.996**	**0.996**	**1.000**
STFPM	0.994	0.980	0.987	0.986	0.999
CSFlow	0.951	0.974	0.962	0.958	0.992

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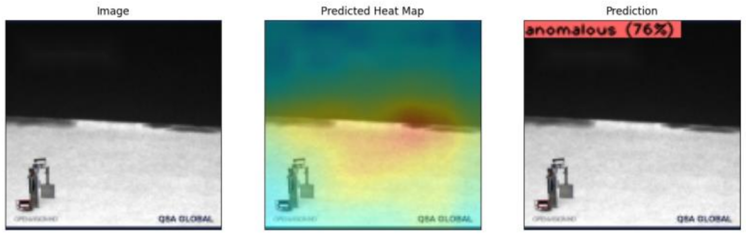
X-Ray Pipeline Damage Detection

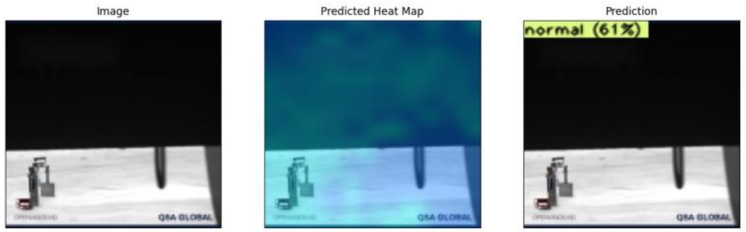
Patchcore [PAT2022] works in the following steps:

- Image patch features are extracted from a pre-trained encoder.
- The features are greedily sub-sampled into a coreset and stored in a memory bank.
- Nearest neighbor search is performed in the memory bank and patch-feature distances are calculated to perform anomaly detection and anomaly localization.

Patchcore Abnormal Inference Example:



Patchcore Normal Inference Example:



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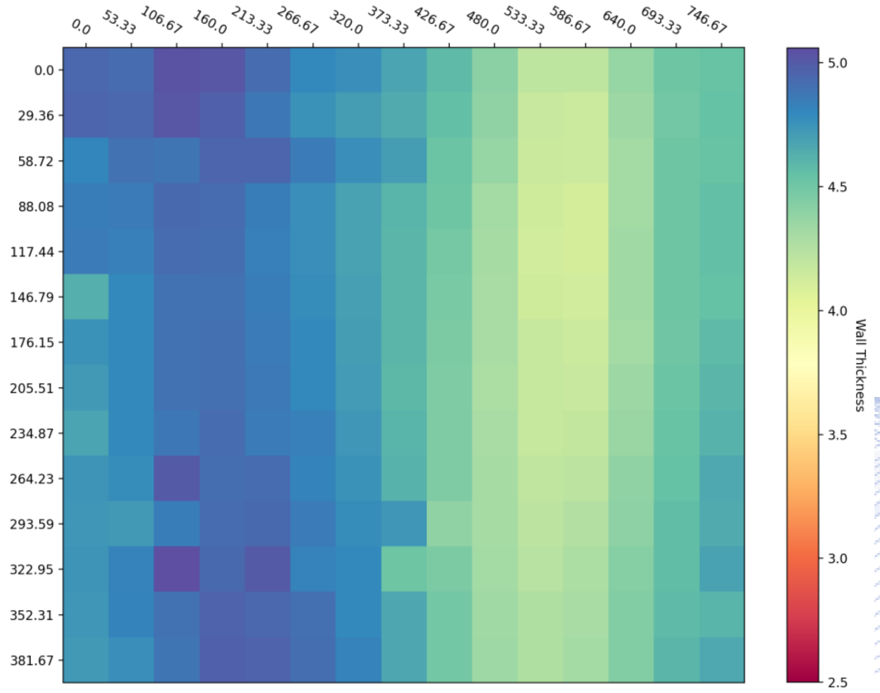
PEC Pipeline Damage Detection

- The PEC sensor measures the remaining pipeline thickness and the percentage of wall loss determines the corrosion severity.
- The corrosion level scale was established as follows:

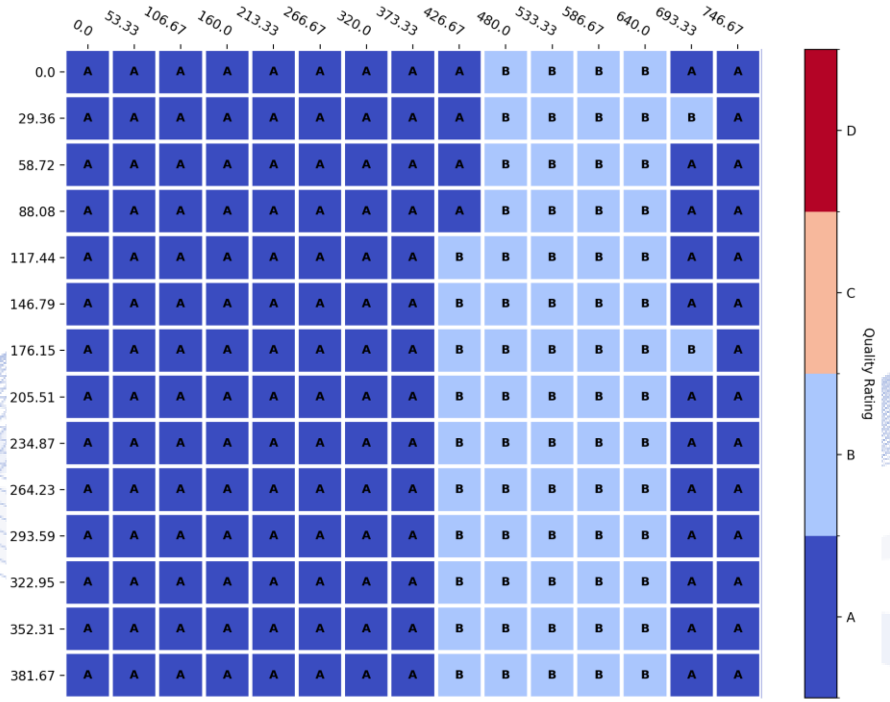
1. Level A (Zero Corrosion): Wall thickness loss < 10%.
2. Level B (Low Corrosion): Wall thickness loss 10-30%.
3. Level C (Medium Corrosion): Wall thickness loss 30-50%.
4. Level D (High Corrosion): Wall thickness loss > 50%.

PEC Pipeline Damage Detection

- The developed Corrosion Level Detection (CLD) localizes the corroded areas based on the established corrosion severity scale.



PEC measurement



Output of the CLD algorithm

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