AI Enabled Threat Detection in Gas Pipelines using a stereo-vision system

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Overview

- Motivation and Objectives
- Overall Prognostics Pipeline
- Data Acquisition using stereo vision
- Machine Learning for Defect Localization
- Prognostics
- Conclusions
- References

Motivation

- The US has approximately 3mn miles of pipeline infrastructure that transport more than 28 tcf of natural gas every year.
- Rapid infrastructure expansions needs an increase in prognostics efforts.
- Pipeline anomalies such as fatigue cracks, corrosion and welding defects pose a threat to life, property and the energy supply chain.

Columbia Gas Transmission Corp. explosion in Virginia, 2012 was caused due to corrosion and lack of recent inspection. (NTSB) (Source: Metropolitan Environmental)

Report	Incidents	Injuries	Fatalities	Damages ($) (Bn)
Gas Distribution	1094	522	105	1.229
Gas Transmission	1226	108	25	1.315
Hazardous Liquids	3978	26	10	2.812
Total	6298	656	140	5.356

Summary of pipeline incidents in the last decade. (Source: PHMSA)

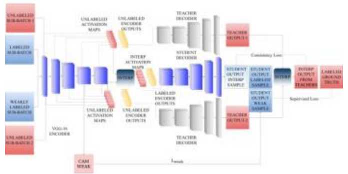
Objectives

Design	Propose	Propose	Evaluate
Multi-sensor autonomous In-Line Inspection (ILI) system	Multi-modality information fusion technique for threat detection.	Learning algorithms for limited labeled data and concept drift under uncertainty	Structural health of the pipeline using the acquired data to predict key features such as remaining useful life

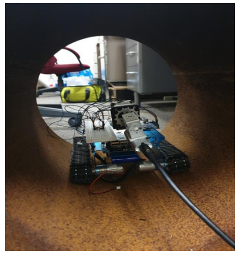
Overall pipeline for defect detection and prognostics

Machine Learning & Image Processing Techniques

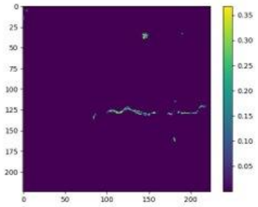
Raw data acquisition



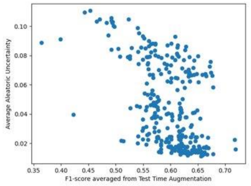
Prediction



Feature extraction



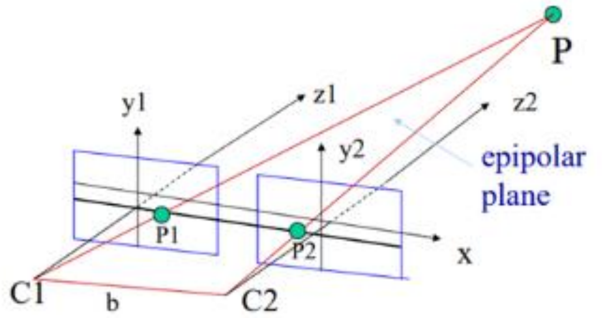
Uncertainty Quantification & risk assessment



Prognostics

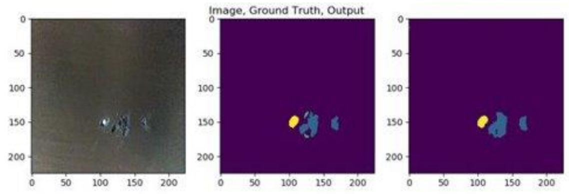
Analytics

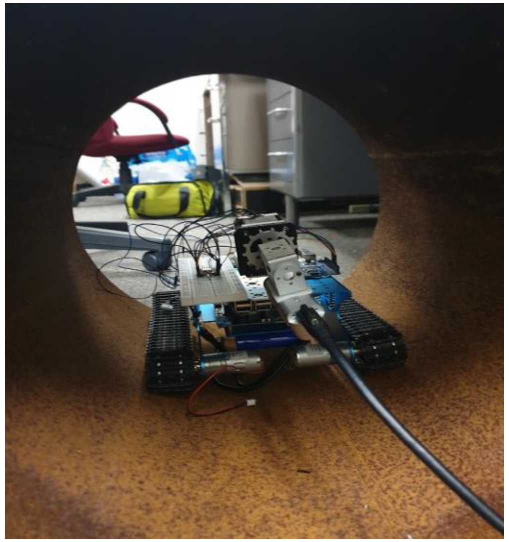
Data Acquisition using Stereo Vision



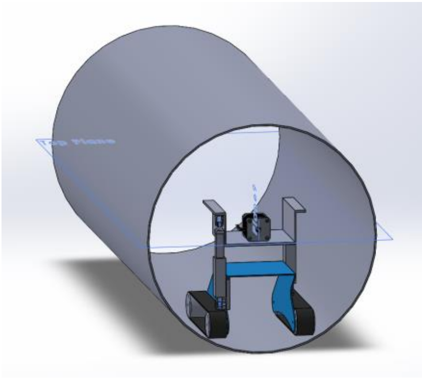
Raw depth data is acquired using "active" stereo vision: Binocular stereo + IR Dot Projection for "fake textures"

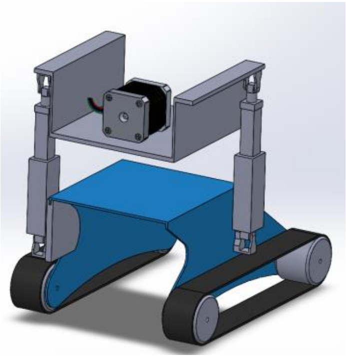
Intel Realsense ™ D435i camera

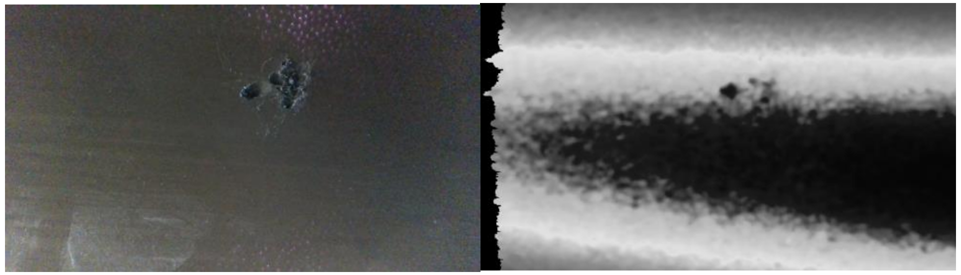




Wired RGB-D camera that captures pipe wall features at 1280x720 pixels and 30fps.



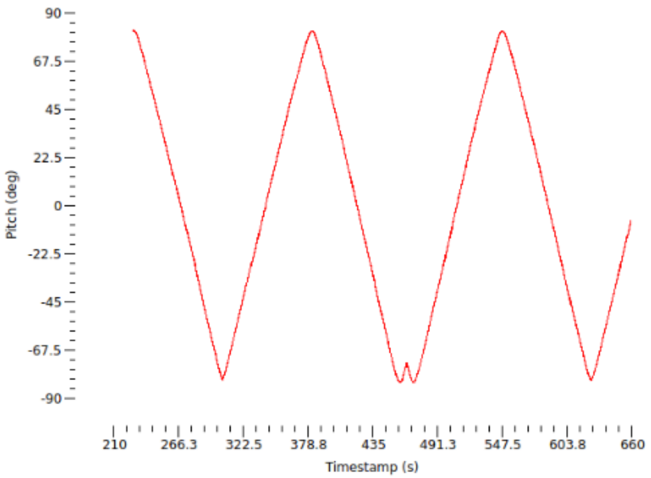




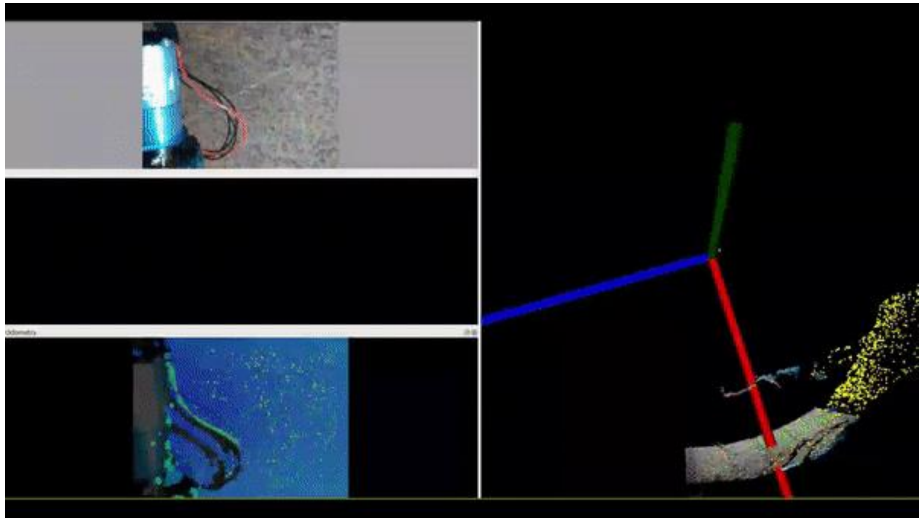
RGB-D data from a plastic pipe sample

Defect Localization and Pipe Mapping

- RGB-D SLAM
  - Capturing fine details of the pipe during the scanning process.
  - Defect localization using IMU-Visual Odometry fusion
- Challenges:
  - Featureless surfaces can cause high uncertainty in robot position
  - Jerky movements can exacerbate these problems.
- Solutions:
  - Using additional sensing elements (Eg: stepper motor data) to inform camera angle.



Tracking the camera angle as it scans the pipe surface.



Pipe mapping demonstration for a corroded metallic pipe using the RTAB-Map package, that performs RGB-D Simultaneous Localization & Mapping (SLAM)

Machine Learning for Defect Localization

- Learning with Limited Data: Semi-Supervised Defect Localization using Activation Map Interpolation
- Uncertainty Quantification for Defect Localization in limited data situations

Learning with Limited Data: Semi-Supervised Defect Localization using Activation Map Interpolation

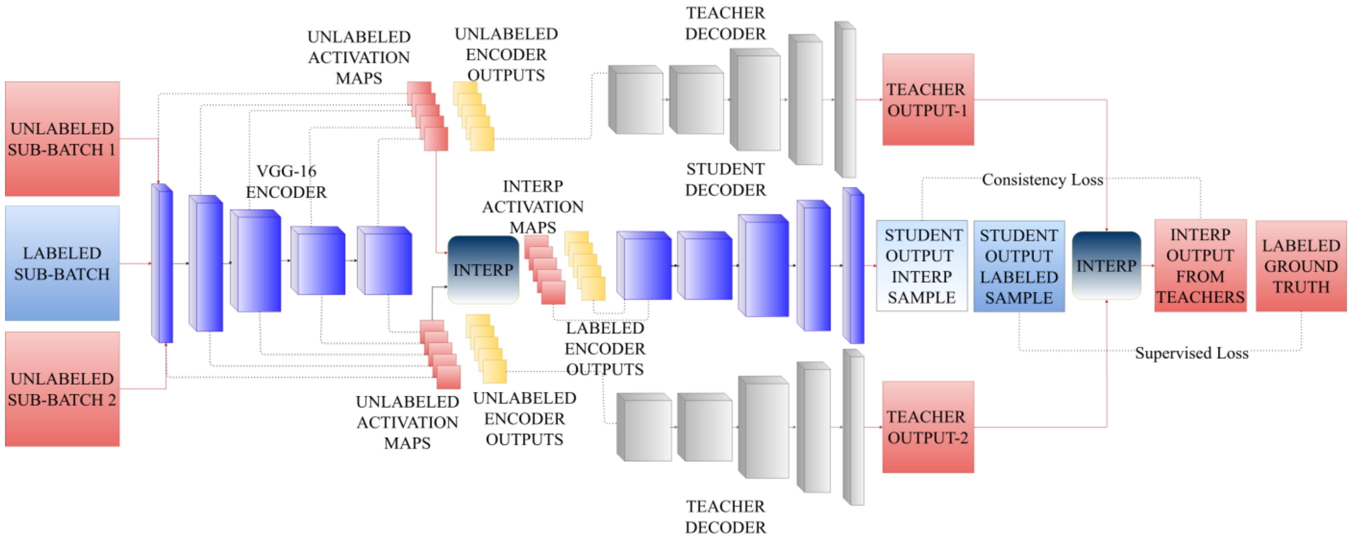
- Industrial applications such as SHM and NDT do not often have large training sets of image data readily available.
- Semi-supervised image segmentation: Latent information from unlabeled data can be leveraged using supervision from a limited training set.

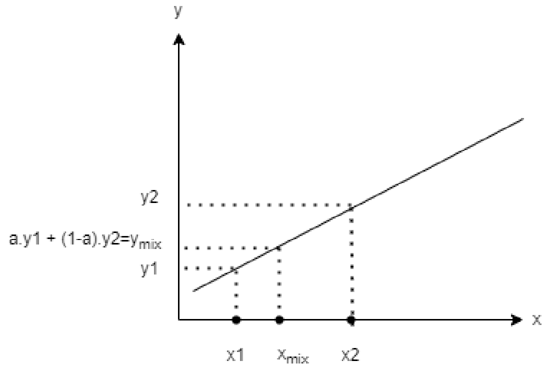
Learning with Limited Data: Semi-Supervised Defect Localization using Activation Map Interpolation

- **Key idea:** Perturb inputs using augmentation to generate samples in the neighborhood of the original sample. Then, constrain the prediction of the neural network for both samples.

$$x_{mix} = a.T_1(x_1 + \epsilon_1) + (1 - a).T_2(x_2 + \epsilon_2)$$
$$y_{mix} \approx a.T_1(y_1 + \epsilon_1) + (1 - a).T_2(y_2 + \epsilon_2)$$

- T_i are image transformations and ϵ_i is a noise function.
- **Interpolation consistency** training: Interpolate between two samples, constrain prediction such that it is also linearly interpolated.



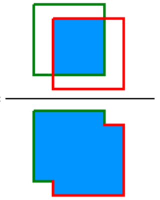


Demonstrative Results – NEU Surface Defects Dataset

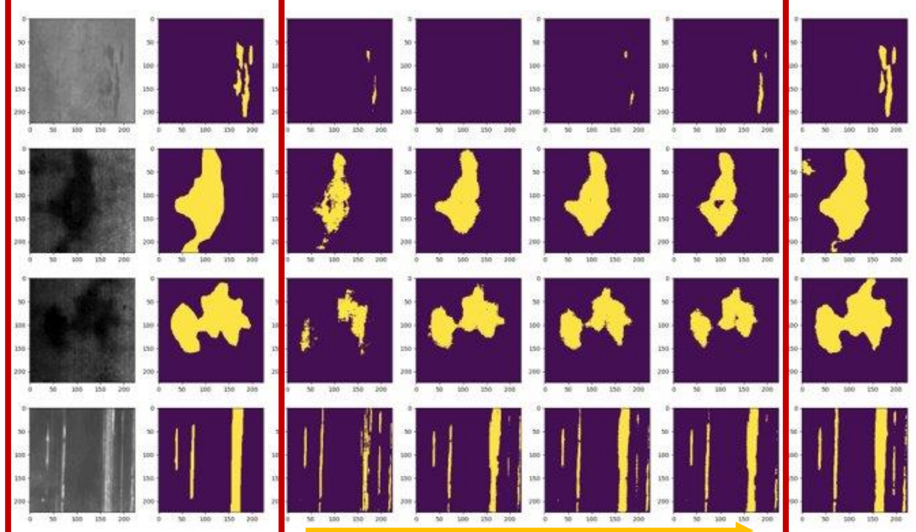
Labeled samples	Supervision	mIU
0%	Consistency Loss Only	0.08
5%	Supervised	0.39
	Semi-Supervised	0.64
10%	Supervised	0.43
	Semi-Supervised	0.66
20%	Supervised	0.51
	Semi-Supervised	0.64
50%	Supervised	0.68
	Semi-Supervised	0.69
100%	Supervised	0.84

Method	Type	Labeled	mIU
SegNet [3]	Fully Supervised	100%	0.5657
PSPNet [29]	Fully Supervised	100%	0.7225
PGA-Net [7]	Fully Supervised	100%	0.8215
Ours	Fully Supervised	100%	0.8309
Ours	Semi-Supervised	5%	0.6429
Ours	Semi-Supervised	10%	0.6674
Ours	Semi-Supervised	20%	0.6454
Ours	Semi-Supervised	50%	0.6992

$$IOU = \frac{\text{area of overlap}}{\text{area of union}} =$$

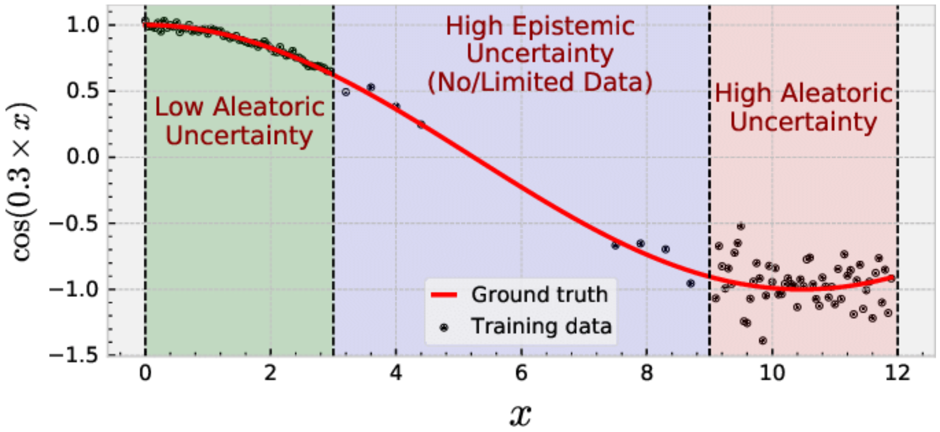


NEU Dataset:
3 defect types, 600 training images in total.
Performance metric:
mIU- mean (over # of classes) Intersection over Union

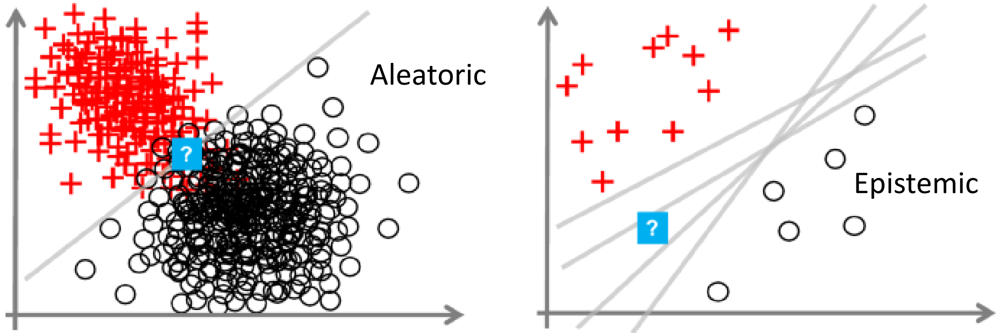


Uncertainty Modeling

- Context:
  - **<u>Can we trust the results?</u>**
    - How would predictions be impacted if there's not enough data?
    - How would predictions be impacted if the test data is different from what we trained on?
  - Key idea: Predict with nuance, in an uncertain and changing world.
  - Classifiers vs Regression models
  - Epistemic vs Aleatoric uncertainty
    - Most types of uncertainty are "reducible".
    - Sources of uncertainty assumed "irreducible":
      - Sensor noise
      - Occlusion, reflections and other image artifacts



Uncertainty in regression
DOI:10.1109/AITEST52744.2021.00027



Uncertainty in classification
DOI: https://doi.org/10.1007/s10994-021-05946-3

Uncertainty Quantification for Defect Localization in limited data situations

- MC-Dropout FCN:
  - A form of model averaging by changing model complexity randomly over multiple sampling iterations.
  - Key Idea: Modify the deep neural net by adding in a dropout layer and use the dropout layer during inference to randomly remove model parameters to get an averaged output from multiple models.

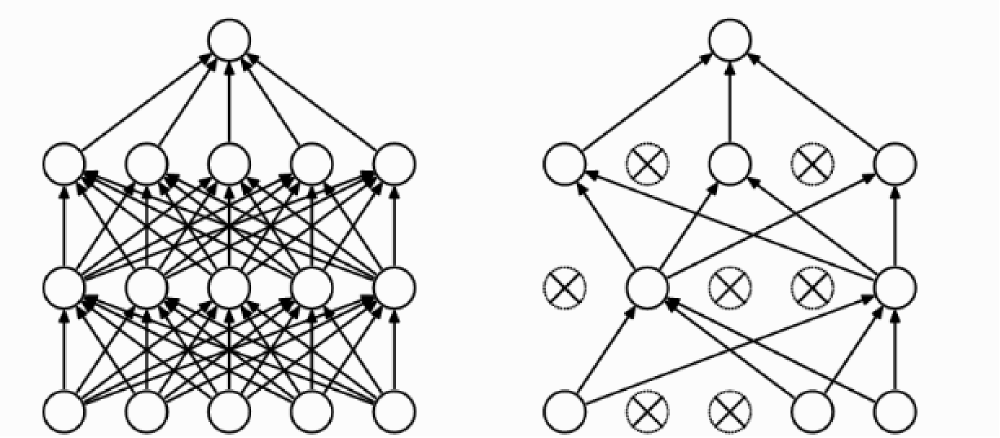


Illustration of dropout in neural nets*
(source: https://proceedings.mlr.press/v48/gal16.html)

Uncertainty Quantification for Defect Localization in limited data situations

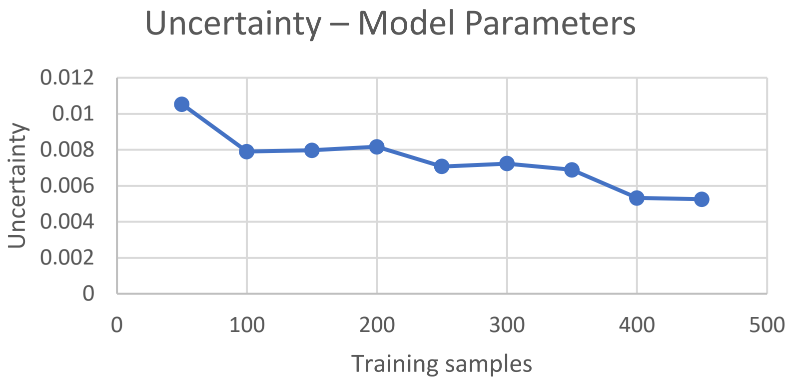
- Uncertainty modeling using entropy

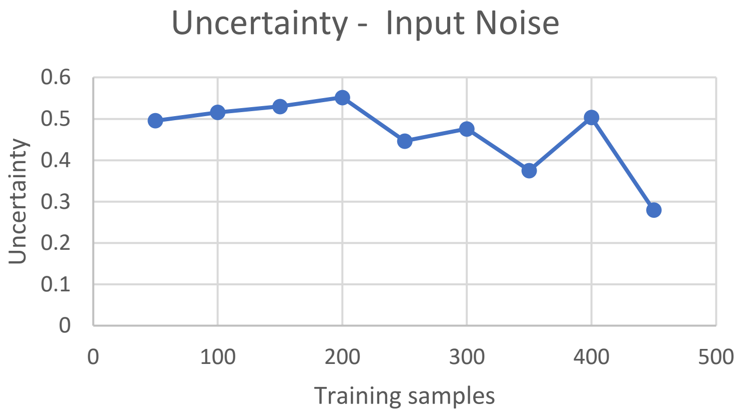
$$U = -\sum_{c=1}^{C} p_i log\, \mathrm{p_i}$$

- Uncertainty sources considered in the present model:
  - Uncertainty in the model parameters – Reducible with more data
  - Uncertainty due to the input – Sensor noise
- Both uncertainties are modeled using the entropy function

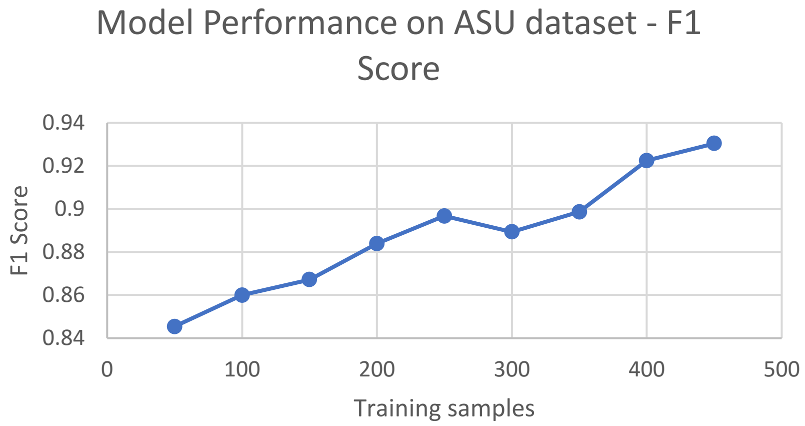
Demonstrative Results

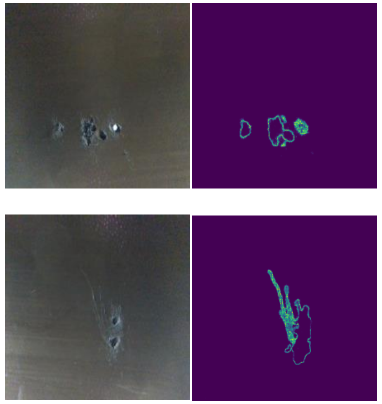
Demonstration on the ASU pipe defect dataset





- Our dataset consists of 3 types of defects: Cracks, pits and (very rarely) holes.
- A dataset of 14 images was augmented to create 600 images.

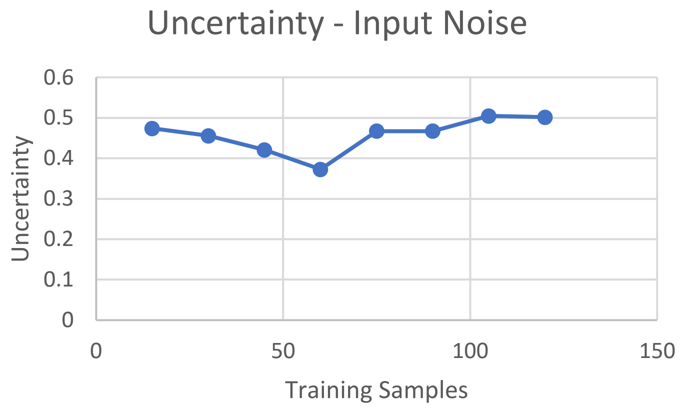


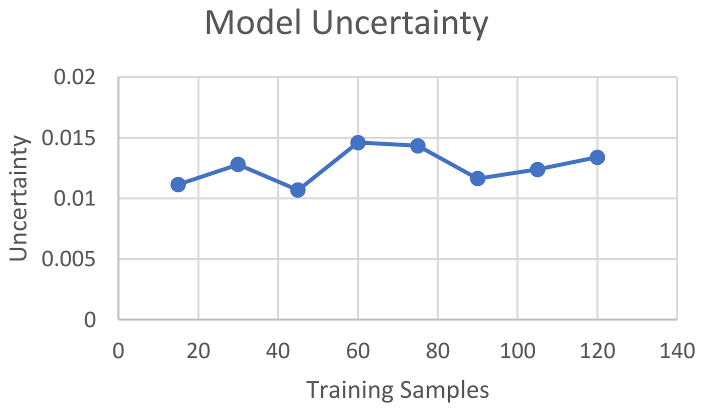


- Most of the uncertainty is in the boundary of the defect
- Segmentation uncertainty from the model is not expected to strongly affect defect area measurements.

Demonstrative Results

- Cross-Dataset training – Road Cracks to Concrete Cracks

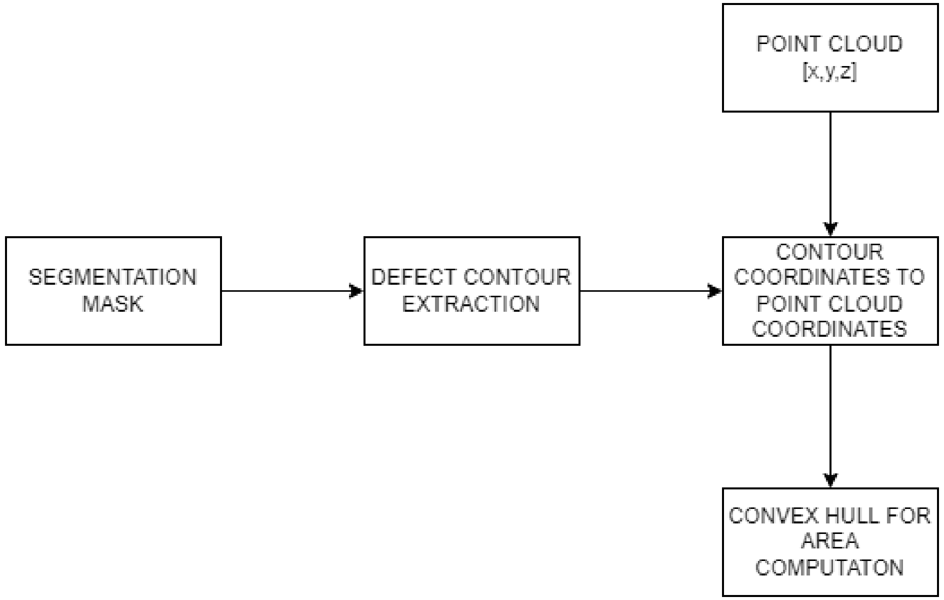




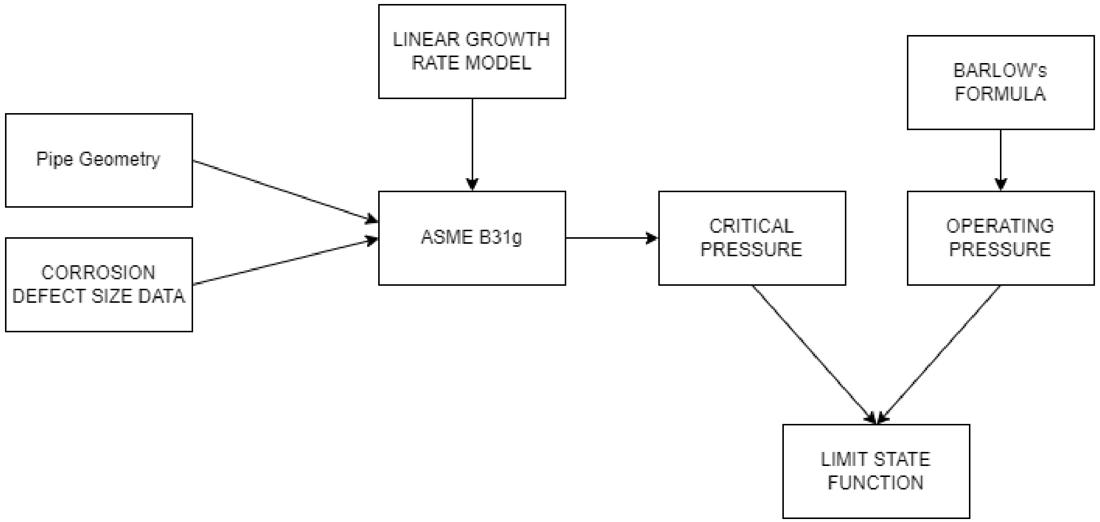
Defect Measurement from Segmentation

Image	Defect Type	Measurement	Estimated (mm/mm2)	Actual (mm/mm2)	Error(%)
	Pitting	Area	2603	2375	8.76
		Depth	0.001	~2	~100
	Cracking-1 Root Middle	Length	71.9	78	8.48
		Width	2	1	~100
	Cracking – 2 Root Left	Length	34.7	37	6.62
		Width	3	1	~200
	Cracking – 3 Root Right	Length	50	56	12
		Width	3	1	~200

Demonstrative example of measuring defect sizes using the 3D point cloud obtained from the D435i camera



Prognostics and Remaining Useful Life Estimation



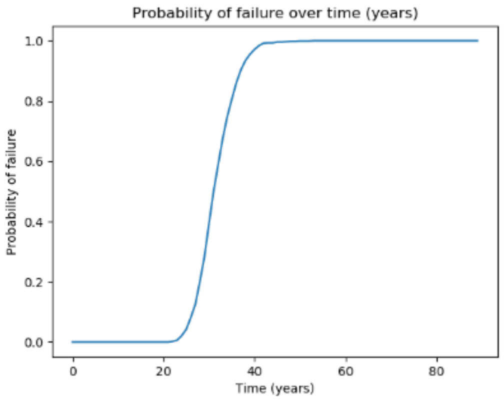
Barlow's formula: $P_{op} = 2 * t * \frac{S_y}{D}$

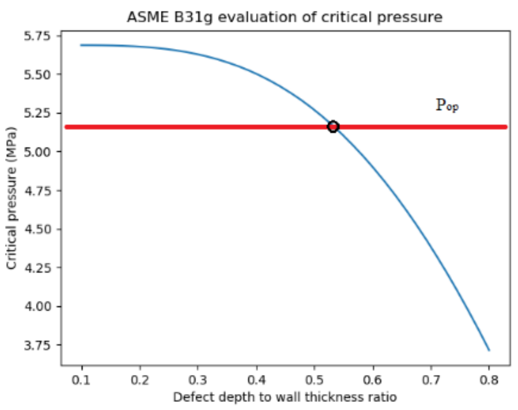
ASME model for critical pressure

$$P_f = \frac{1.1 S_y 2t}{D}\left(\frac{1 - 0.85\left(\frac{d}{t}\right)}{1 - \frac{0.85\left(\frac{d}{t}\right)}{M1}}\right)$$

$$M1 = \sqrt{1} + 0.6275z - 0.003375z^2, z = \frac{L^2}{Dt} \leq 50$$

$$M1 = 0.032z + 3.3, z = \frac{L^2}{Dt} > 50$$





Corrosion pitting defects: Critical Pressure Calculation

- ASME B31g model for corrosion pitting failure pressures.
- Monte-Carlo simulations with growth rate and defect size variances to produce n possibilities to compute reliability using the limit state function.

Conclusions

- Depth information provides useful data to evaluate defect sizes: The current sensor can quantify millimeter scale defects.
- RGBD-SLAM with odometry was used for online mapping of the pipe surface:
  - Current limitations include textureless surfaces where the uncertainty in position estimates from the visual odometry is high and cannot compensate for the variance in IMU odometry.
  - Proposed solution: Integrate stepper motor data to the odometry inputs for additional orientation information with low uncertainty.
- Semi-supervised learning based on consistency regularization can help with using limited labeled data to train a model that can localize defects.
- Uncertainty quantification using entropy as a metric shows that the epistemic uncertainty reduces with more training data.

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Thank you for your attention.

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