Machine Learning-based Anomaly Detection with Magnetic Data

ML4Eng Paper

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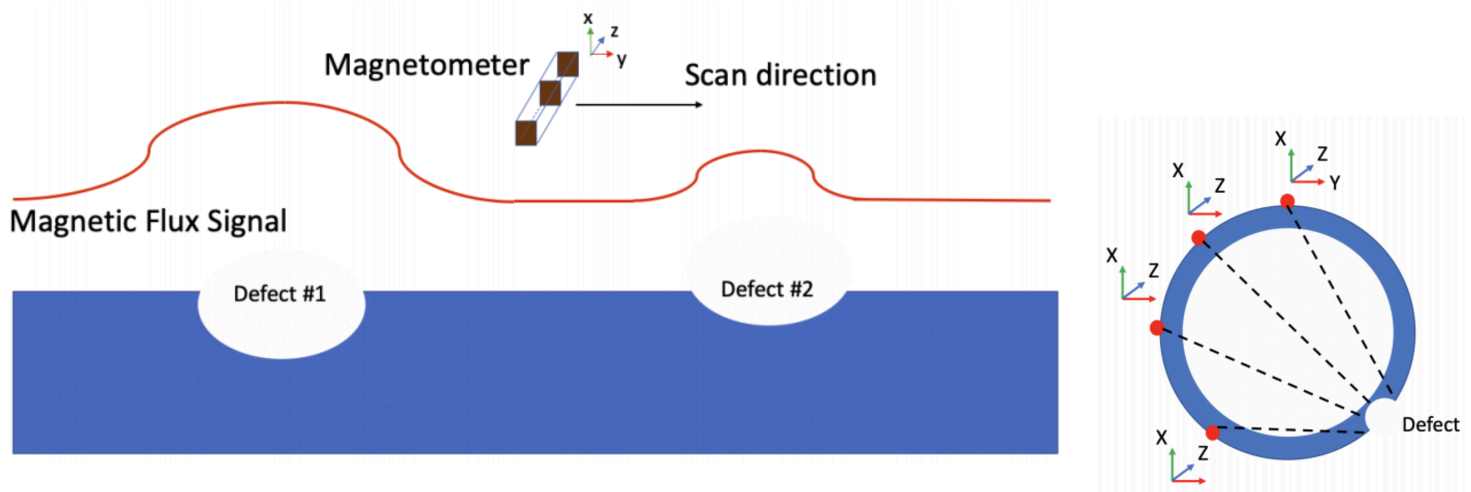
TOTAL

by Computational Science Engineering
Data Science & Artificial Intelligence

NEURAL INFORMATION PROCESSING SYSTEMS

Motivation

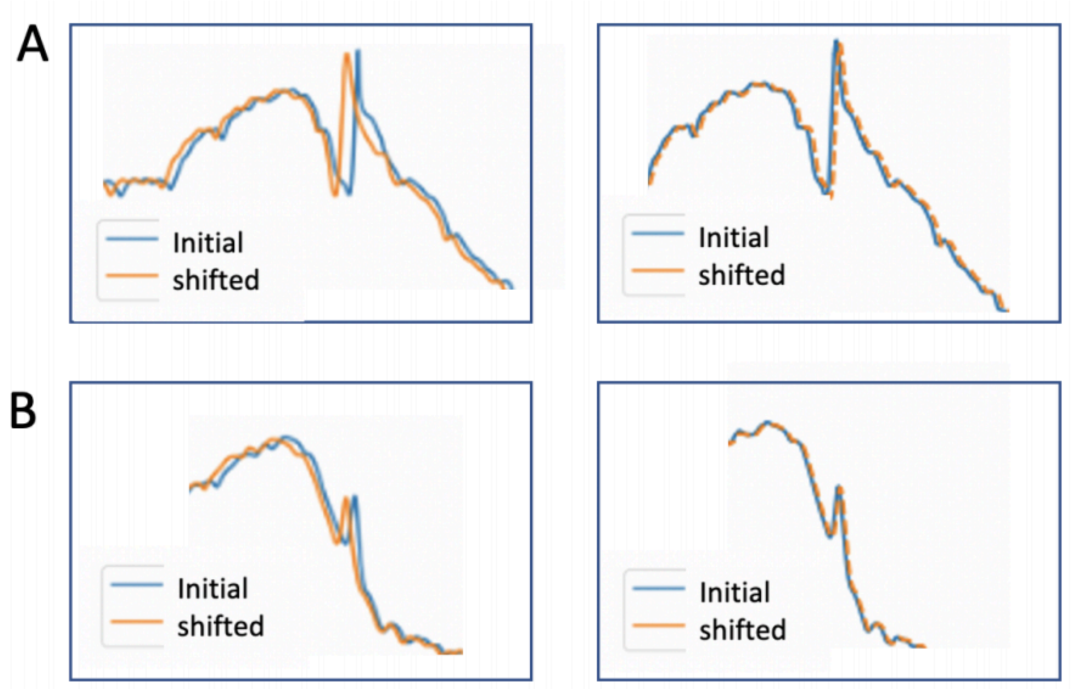
- Pipeline Integrity important to the energy industry
- Undetected defects can cause significant damage
- Intrusive methods cause operational challenges
- Non-intrusive magnetic methods like LSM are promising in detecting/characterizing pipeline defects
- Anomaly detection from multi-sensor, multi-alignment LSM data not trivial
- Study to explore Scalable ML methods for this task



Schematic of LSM technology showing data collection across multiple sensors, and gathers data in all three spatial directions

Data and Preprocessing

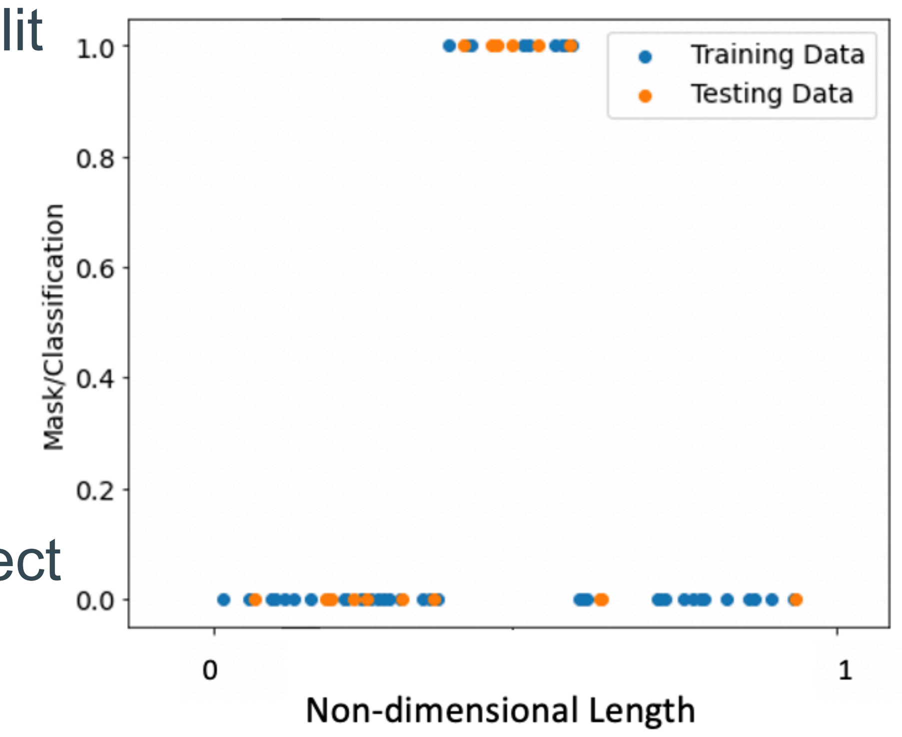
- Multi-sensor LSM data are multi-modal, non-aligned sequences, that affects ML model predictions
- Fast Dynamic Time Warping algorithm re-aligns dataset with O(N) time and space complexity



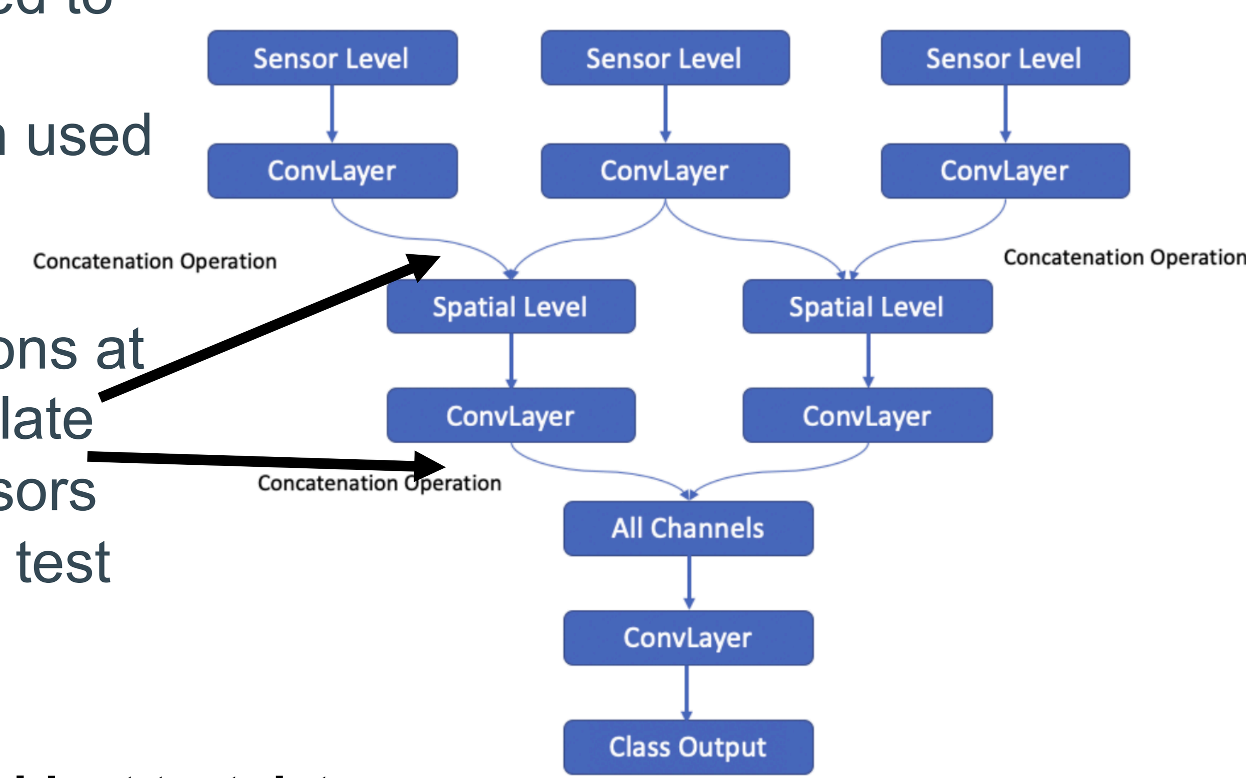
Defect	Location	Volume	Depth	Width
D1	2 ft	0.2	0.77	0.45
D2	76 ft	0.6	0.62	1

Customized 1D CNN for multi-output prediction

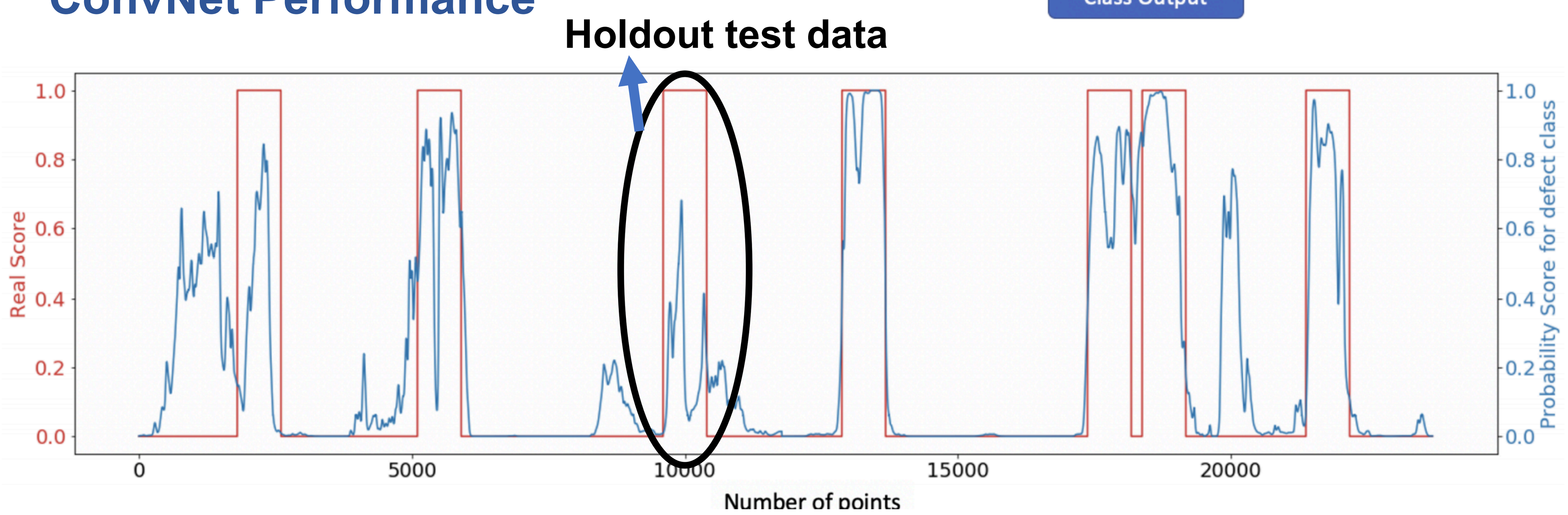
- Data leakage in random test/train split
- Masked defect regions with +/- 10 ft
- **Train samples:** 35000
- **Test samples**: 10000



- The "point-based" methods can detect defect, but not characterize them
- Sequence learning using CNN with 1D filters used to extract spatial features
- Multi-task classification used to characterize defect properties
- Concatenation operations at the spatial levels to isolate effects of different sensors
- One defect held out as test dataset



ConvNet Performance

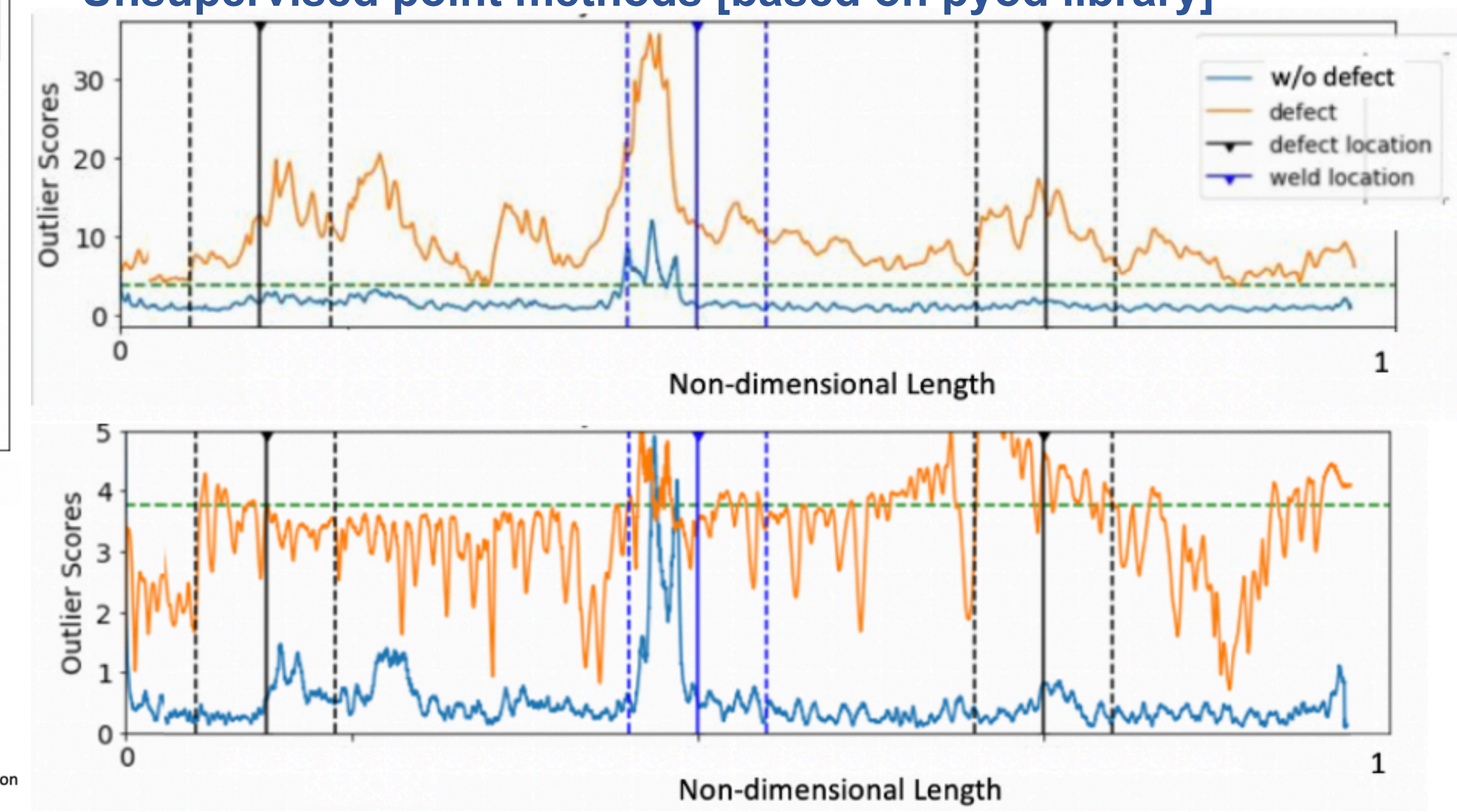


TL;DR

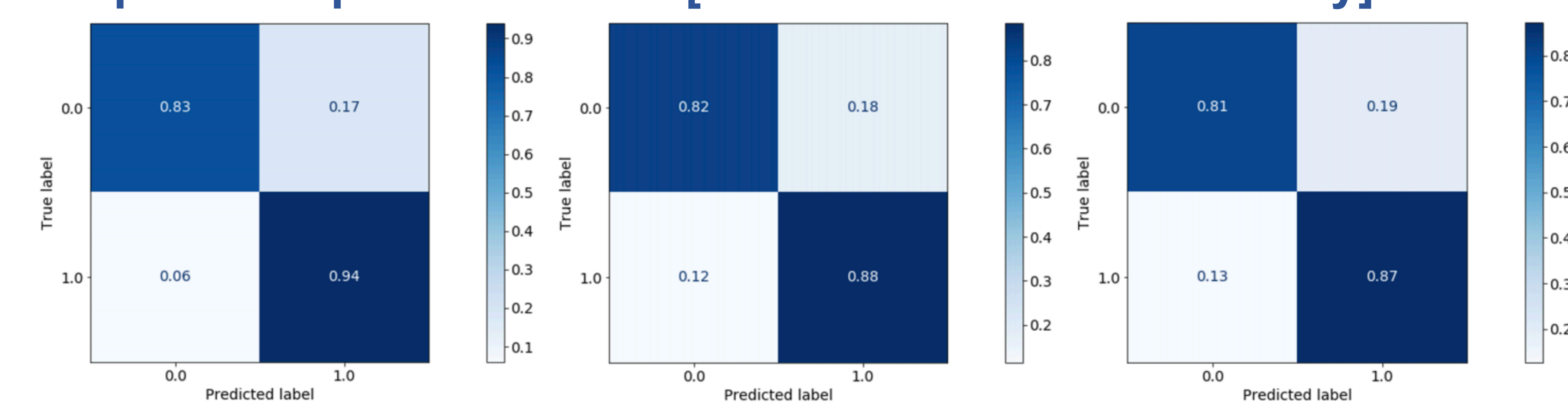
- Robust multi-sensor data alignment using FastDTW achieved
- Point-based supervised/unsupervised learning methods identify defects successfully.
- Slower methods sped up using RAPIDS-AI cuML library
- Multi-output CNN techniques are useful tools for characterizing defects
- Feasibility for field data explored and suitable methods identified

Off-shelf ML packages

Unsupervised point methods [based on pyod library]



Supervised point methods [based on scikit-learn library]



SVC | Decision Trees | MLP Classifier

Training time

- N = 10000 points
- All times in seconds
- SVC is slowest!

Algorithm	N	10*N	100*N
k-NN	1.47	11.2	140
SVC [rbf]	8.76	751	18274
Decision Trees	0.33	3.86	131
MLP Classifier	7.9	69	772

Speed up of SVC [RBF kernel] using RAPIDS-AI cuML library

Data points	scikit–learn	RAPIDS-AI	Speed up
10000	8.76	2.90	3
100000	751	3.75	200
1000000	18274	98	186

References

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- Yue Zhao, Zain Nasrullah, and Zheng Li. Pyod: A python toolbox for scalable outlier detection. *arXiv preprint arXiv:1901.01588*, 2019.

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