Cavity Detection in Composite Pipe using Machine Learning Methods

Guoyang Shen, Graduate Student

Department of Mechanical Engineering, Cullen College of Engineering

Problem Statement

Composite materials are often used in the **repair** or **reinforcement** of pipelines. Detecting cavities within these repairs is crucial for preventing **leaks** or **failures**, which can have severe environmental and economic consequences. Here in this experiment, a 12" long, 8" diameter aluminum pipe was machined with three different sized circular cavities (1", 1.5", and 2") across parts of its surface. After breaking all sharp edges, 8 layers of fiberglass were used to covered the exterior. The tube is divided into approximately 1"x1" squares along the surface, and tapping sounds were collected and analyzed.

Brief Literature Review

Nowadays, filament-wound GRE pipes are used in a number of industries such as aerospace, oil and gas etc. due to the good corrosion resistance and high strength to weight ratio. [1]

Experimental Setup and Collection of Data

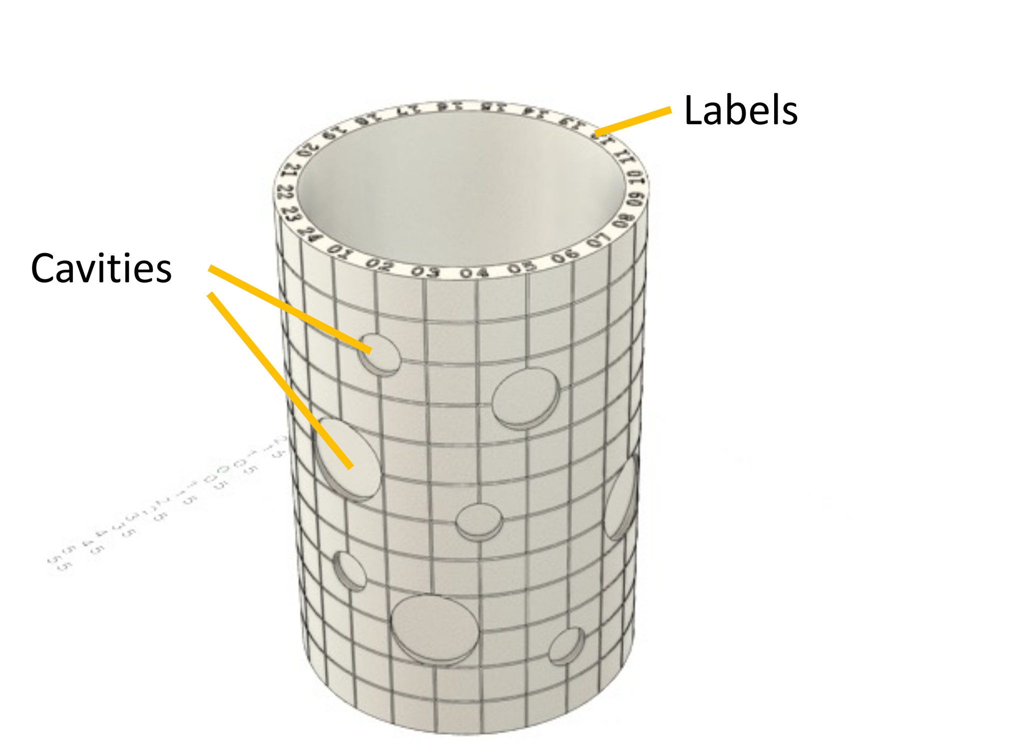


Figure: tube with cavities before wrapped around in fiberglass shells

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1																							
2		1									3			1								3	
3					2												3						
4																				1			3
5	3											3				2							
6				1																		1	
7								3											3				
8	1									1						1							3
9			3										2										
10						1																	

Figure: Cavity distribution map, depth ~0.2"

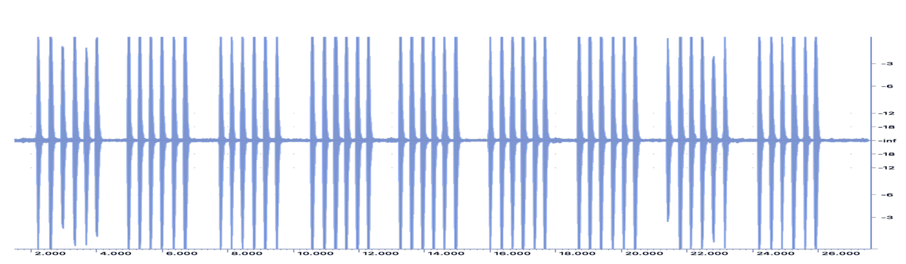


Figure: Multi-point multi-hit audio signal (after noise-cancelation)

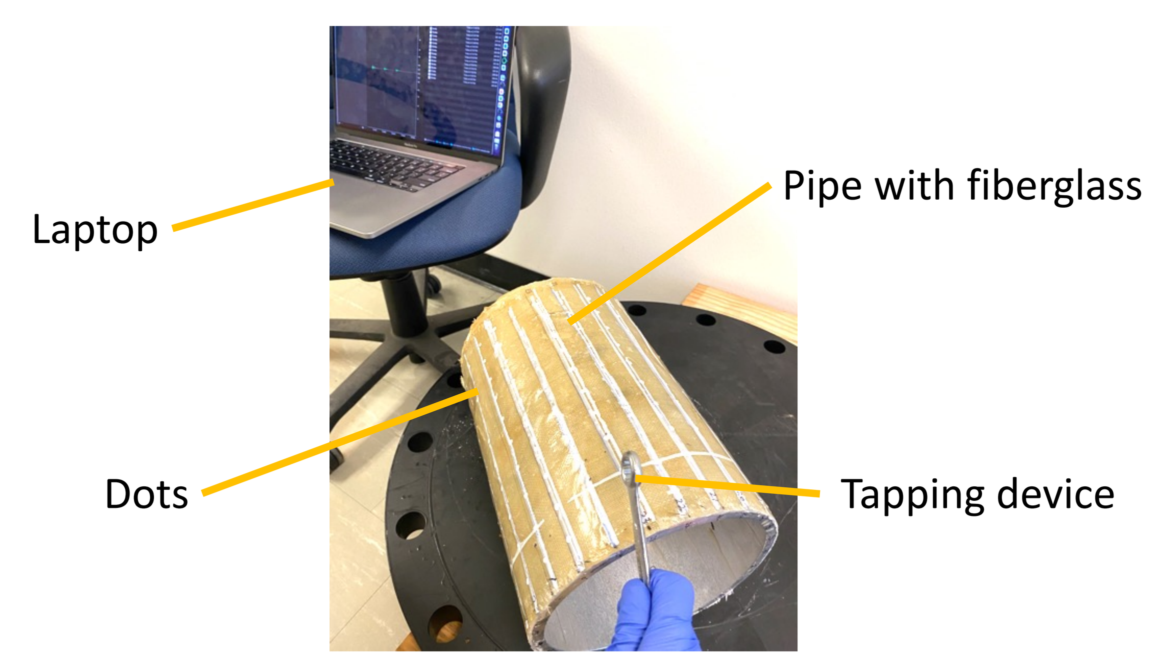


Figure: Data collection process

Method(s)

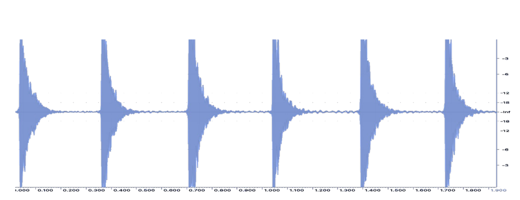


Figure: audio collection

$$MFCCs = DCT\left(\log\left(MFB\left(\left|FFT\left(Window\left(Frame(s)\right)\right)\right|^2\right)\right)\right)$$

Training model using SVM and DT

Applying SVM and DT on validation data

Analyze results and compare with other methods
In deep learning or unsupervised learning

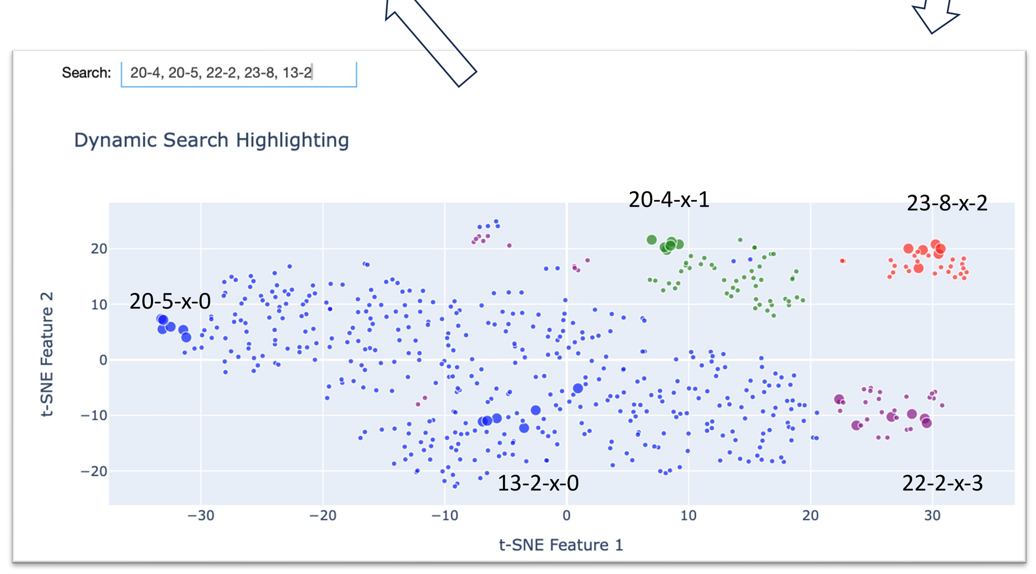
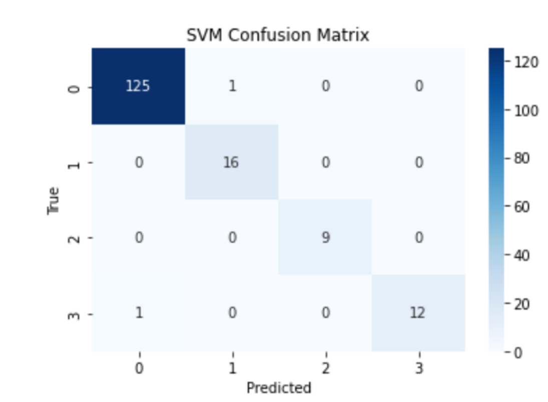


Figure: t-distributed Stochastic Neighbor Embedding plot with search bar

Results, Analysis and Discussion

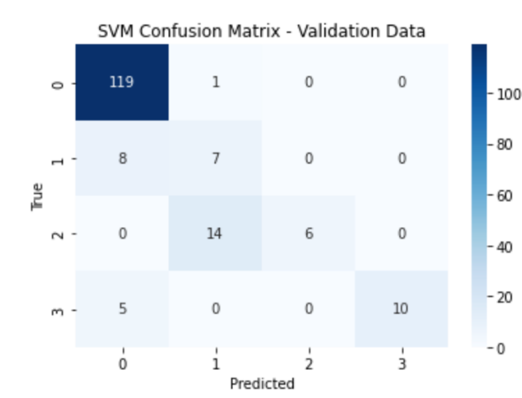
Support Vector Machine Classifier:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	126
1	0.94	1.00	0.97	16
2	1.00	1.00	1.00	9
3	1.00	0.92	0.96	13
accuracy			0.99	164
macro avg	0.98	0.98	0.98	164
weighted avg	0.99	0.99	0.99	164



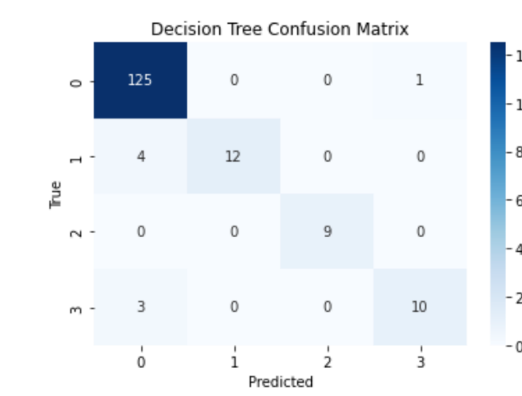
Classification Report for SVM on Validation Data:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	120
1	0.32	0.47	0.38	15
2	1.00	0.30	0.46	20
3	1.00	0.67	0.80	15
accuracy			0.84	170
macro avg	0.80	0.61	0.65	170
weighted avg	0.87	0.84	0.82	170

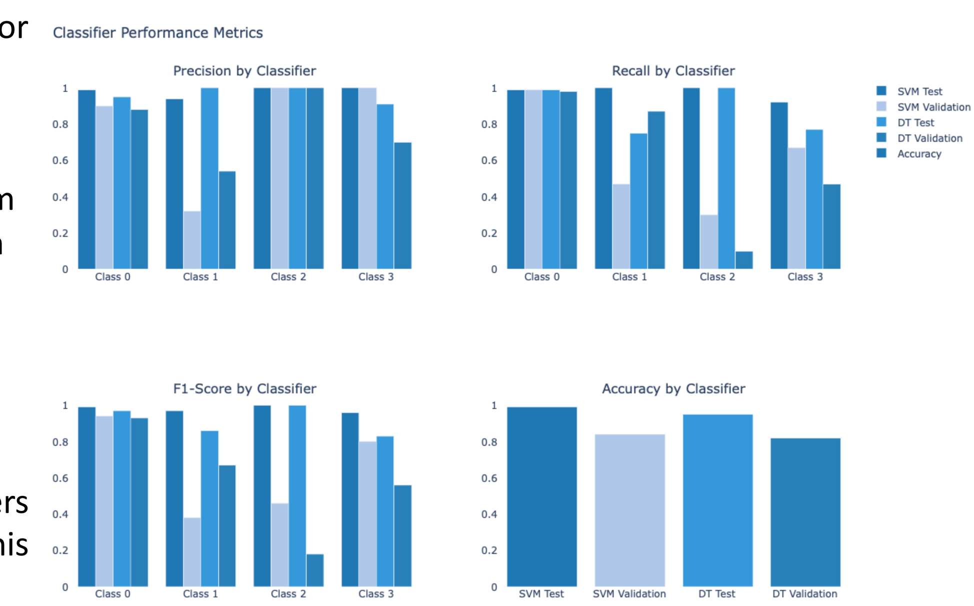


Decision Tree Classifier:

	precision	recall	f1-score	support
0	0.95	0.99	0.97	126
1	1.00	0.75	0.86	16
2	1.00	1.00	1.00	9
3	0.91	0.77	0.83	13
accuracy			0.95	164
macro avg	0.96	0.88	0.91	164
weighted avg	0.95	0.95	0.95	164

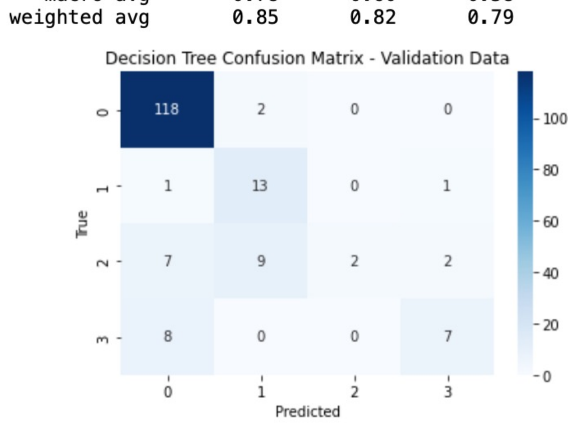


The accuracies were all quite good for SVM (84%) and DT (82%). The precisions were okay. The recall and F1-scores were not so good. The problems might've rooted from from how the epoxy pipe was made, such as resin accidently got into the cavities, the cavities were not deep enough, the fiberglass was bent on top of the large cavity holes etc. However, it should be noted that from the CMs, almost all the numbers are +/- 1 away from the diagonal. This might be improved with more data collection and being more careful on the manufacturing step.



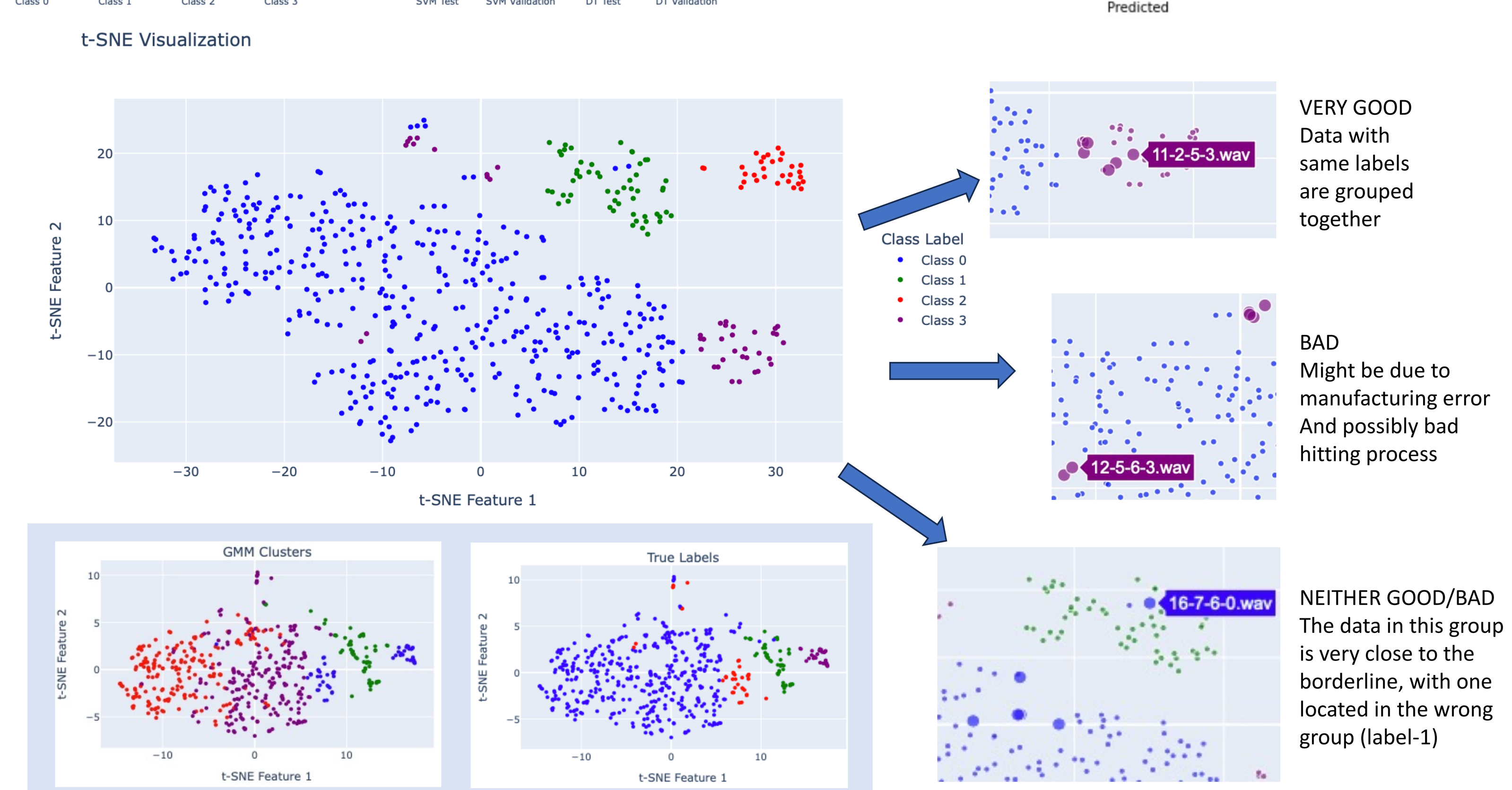
Classification Report for Decision Tree on Validation Data:

	precision	recall	f1-score	support
0	0.88	0.98	0.93	120
1	0.54	0.87	0.67	15
2	1.00	0.10	0.18	20
3	0.70	0.47	0.56	15
accuracy			0.82	170
macro avg	0.78	0.60	0.58	170
weighted avg	0.85	0.82	0.79	170



More findings and patterns can be seen from the t-SNE plots (right figures), where all the labeled points are clustered.
Some cropped areas are shown to show what's a good set and what isn't. The bad set might've had the cavity filled with resin by accident.

Just for fun, GMM (4 components and full covariance) was also used to experiment with the clusters. But the model has trouble distinguishing label-2 and label-3 data. And instead, divided label-0 data into two big parts.



Conclusion

- This study shows that supervised machine learning techniques such as SVM are quite effective and can be used to detect cavities in a resin-fiberglass-covered aluminum pipe. Other methods such as DT and RF (not shown here) can work but not as well as the SVM in this case.
- An interactive t-SNE visualization app made using Plotly and Jupyter Notebook is used to help studying the patterns behind the audio features, and also help us see the quality of the sound data collection. For example, if a set of label-3 data are in the cluster of a large label-0 data, something's wrong and improvements need to be made, most likely in the manufacturing process.
- It can also be seen from the clustering map that the four sets can be easily grouped and spotted, thus the clustering methods such as GMM, DBSCAN or k-Means should be looked into future.
- A real-time measuring/clustering webapp could be very useful in the sound collection applications and could be made if more time was given.

Acknowledgements

The financial support from Midstream Integrity Services (MIS) and technical support from Smart Materials & Structures Lab (SMSL) and Artificial Intelligence Lab for Monitoring & Inspection (AILMI) at UH. Machinist Jamar Murray.

References (brief)

1. Mahdavi, Hamidreza, et al. "Damage Energy Evaluation in [55/-55] 9 Composite Pipes using Acoustic Emission Method." Mechanics of Advanced Composite Structures, vol. 2, no. 2, 2015, pp. 127-134