An Audio-based Machine Learning Approach to Acoustics Detection of the Pipeline Inspection Gauge (PIG)

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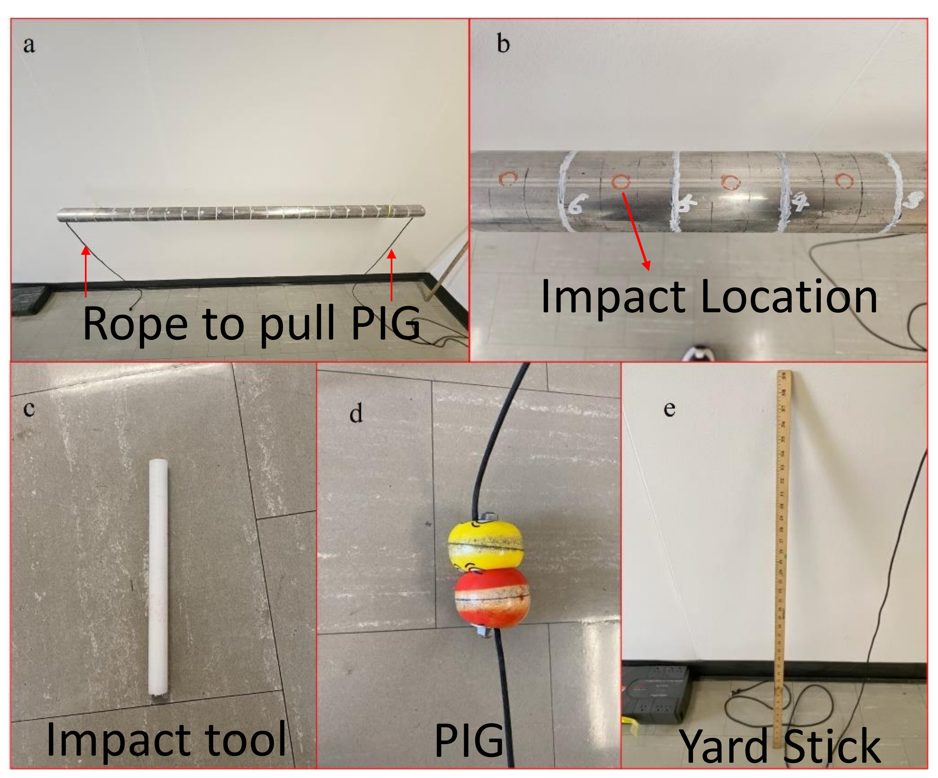
Problem Statement

This project seeks to address the challenge of precisely detecting the location of a Pipeline Inspection Gauge (PIG) within pipelines using acoustic signals. The objective is to determine whether a PIG is present at the knocking location and to accurately estimate the distance between the knocking site and the PIG. By leveraging an innovative audio-based machine learning approach, this research aims to enhance the accuracy and efficiency of PIG localization, analyzing acoustic data generated during pipeline operations to improve maintenance strategies and operational safety.

Brief Literature Review

Traditional PIG tracking methods often lack precision and incur high costs in extensive pipeline networks. Chowdhury and Abdel introduce a cost-effective solution using an inertial measurement unit (IMU), a speedometer, and reference stations to mitigate inertial drift [1]. Bernasconi and Giunta explore acoustic techniques such as cross-correlation analysis and resonant structures to enhance the detection accuracy of PIGs location [2].

Experimental Setup and Collection of Data



Pipe and PIG Setup

Training Data Collection:

Step 1: Move the PIG in the grid between location 3 and 4.

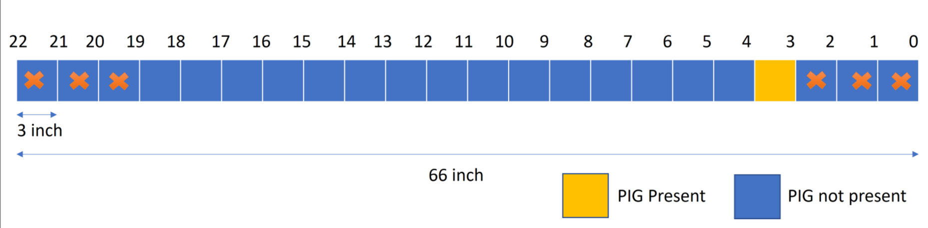
Step 2: Impact on the red circle on the pipe at location between 3 and 4 for 20 times. Save the 20 impacts sound in a single audio file.

Step 3: Next impact on each grid between location 4 to 19 each 10 times consecutively and save the audio in a single file.

Step 4: Do the same for remaining locations.

The data collection for validation data is similar but will less impacts

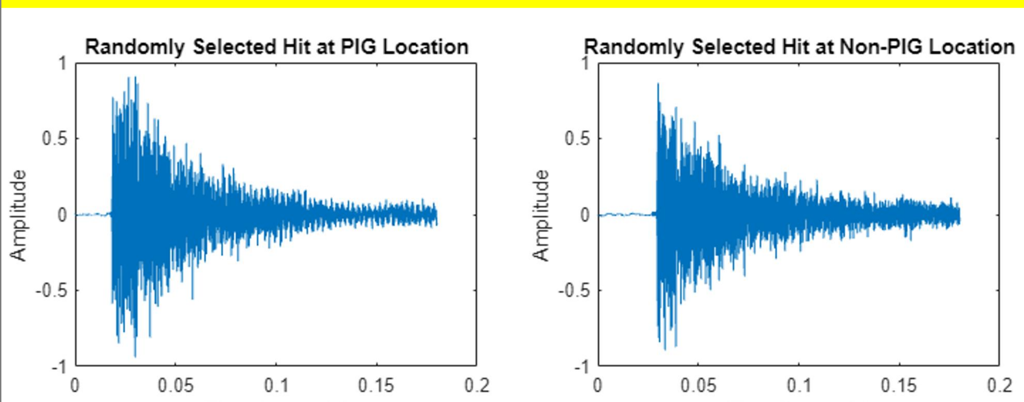
256 audio files for training (2707 single hit)
16 audio files for validation (256 single hit)



t16-6.m4a
t16-6.m4a
Data type: test
PIG location : 16
Knocking location : 6

v8.m4a
v8.m4a
Data type: validation
PIG location : 8

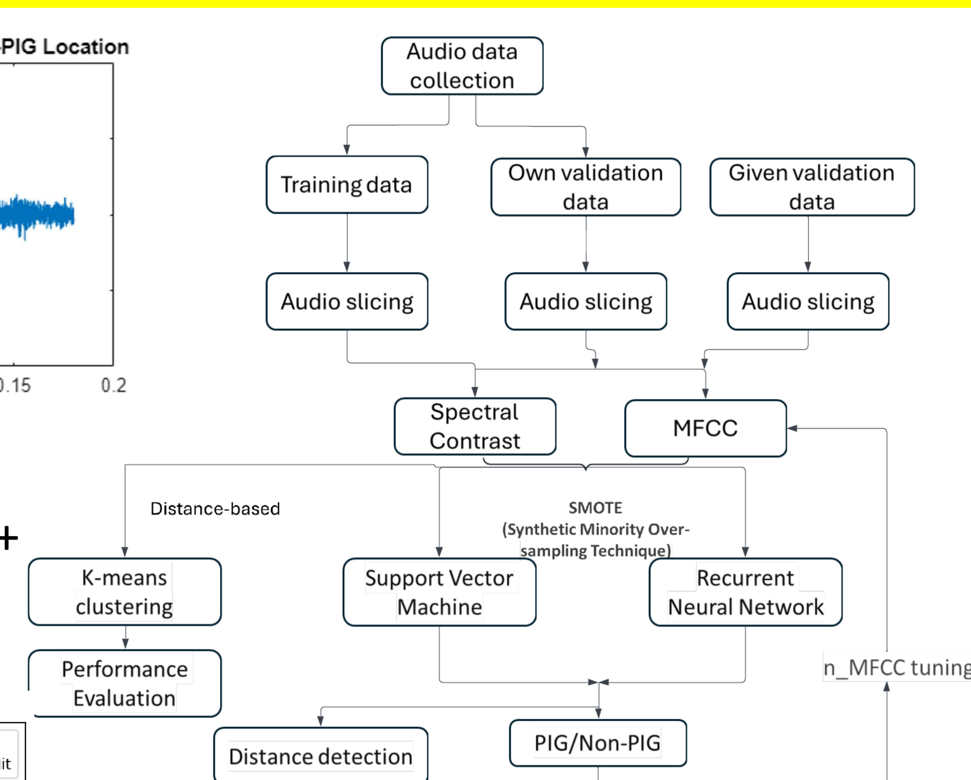
Method(s)



Sliced hit

Signal processing methods: MFCC + Spectral contrast

Extracted features



The number of Mel-Frequency Cepstral Coefficients (MFCC) is optimized based on empirical results to enhance the model's overall performance and ensure robust recall across various labels

RNN

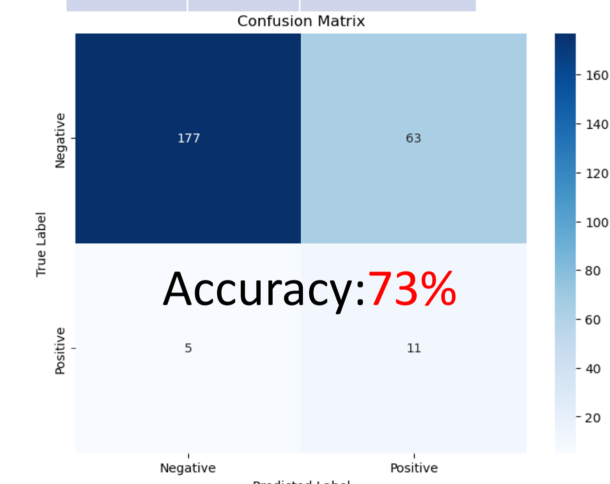
Layers: Sequential model with two LSTM layers.
LSTM Units: 64 units in each LSTM layer
Batch Normalization: Applied after the first LSTM layer
Dropout: Set at 0.5 after each LSTM and Dense layer
Activation: relu for intermediate dense layers and sigmoid for the output layer
Optimizer: Adam with a learning rate of 0.001
Loss Function: Binary crossentropy
Epochs and Batch Size: Configured to 20 epochs and a batch size of 64

SVM

Kernel Type: Linear
Class Weight: Balanced

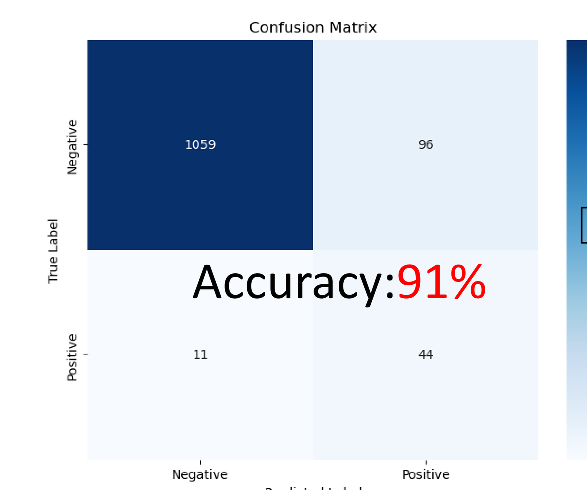
Results, Analysis and Discussion

	PIG	NON-PIG
Recall	0.69	0.74



Confusion Matrix based on our validation data (SVM)

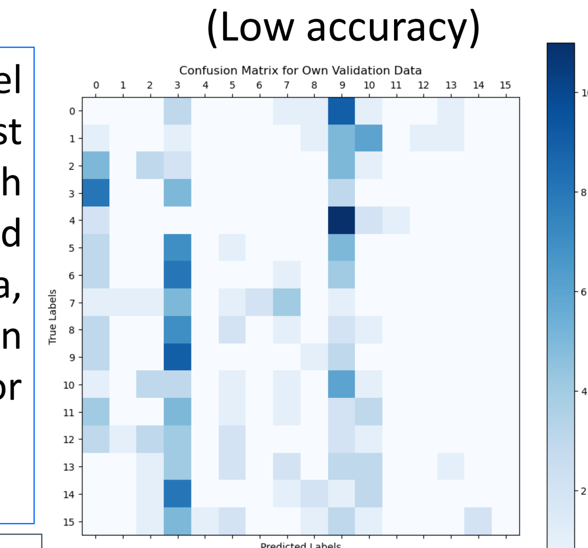
	PIG	NON-PIG
Recall	0.80	0.92



Confusion Matrix based on the provided validation data(SVM)

The SVM model demonstrated robust performance on both our collected and given validation data, especially notable in its high recall rates for PIG/Non-PIG classifications.

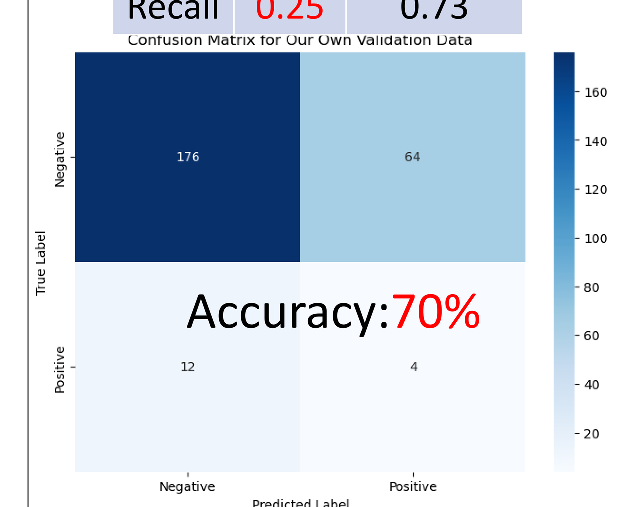
Distance-based classification
(Low accuracy)



Confusion Matrix based on our validation data(SVM)

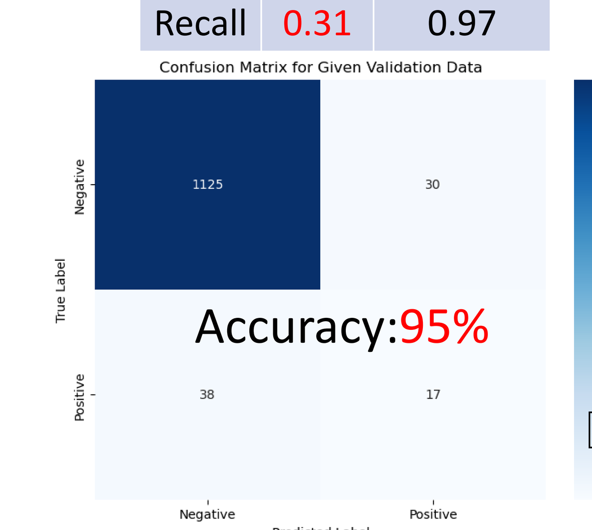
The markedly low accuracy observed in both SVM and RNN models for distance-based classification indicates a potential limitation of extracted features to capture essential acoustic differences associated with varying distances.

	PIG	NON-PIG
Recall	0.25	0.73



Confusion Matrix based on our validation data (RNN)

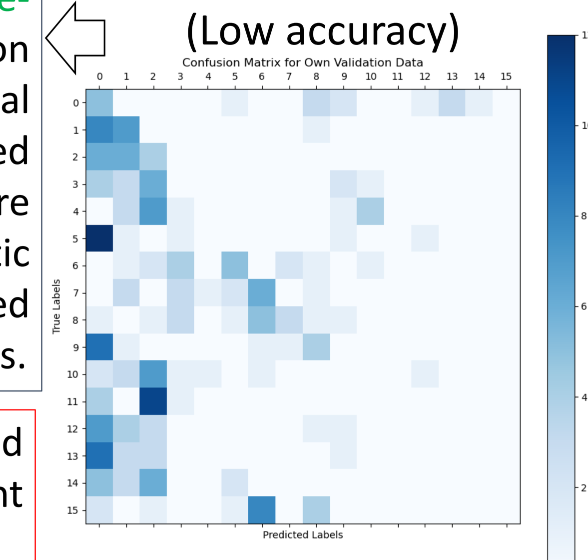
	PIG	NON-PIG
Recall	0.31	0.97



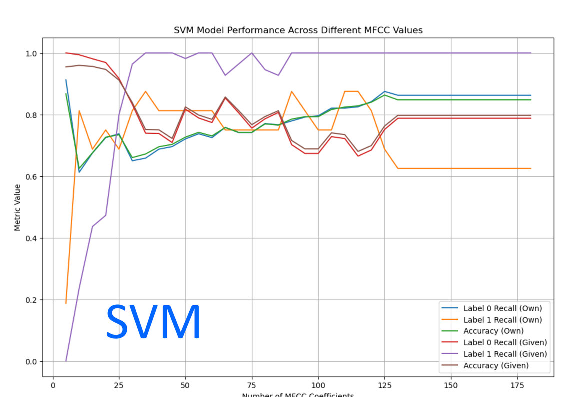
Confusion Matrix based on the provided validation data(RNN)

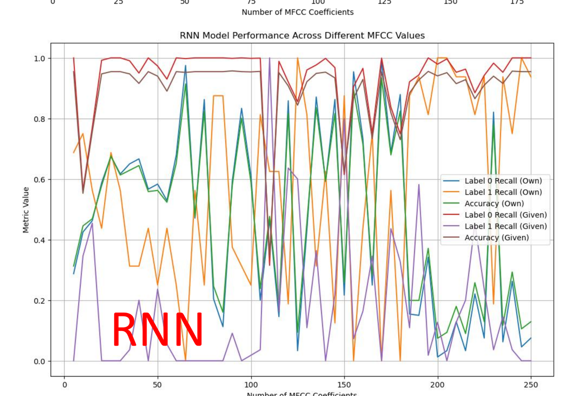
RNN model showed less consistent performance, struggling to maintain a balance between accuracy and recall across the datasets.

Distance-based classification
(Low accuracy)



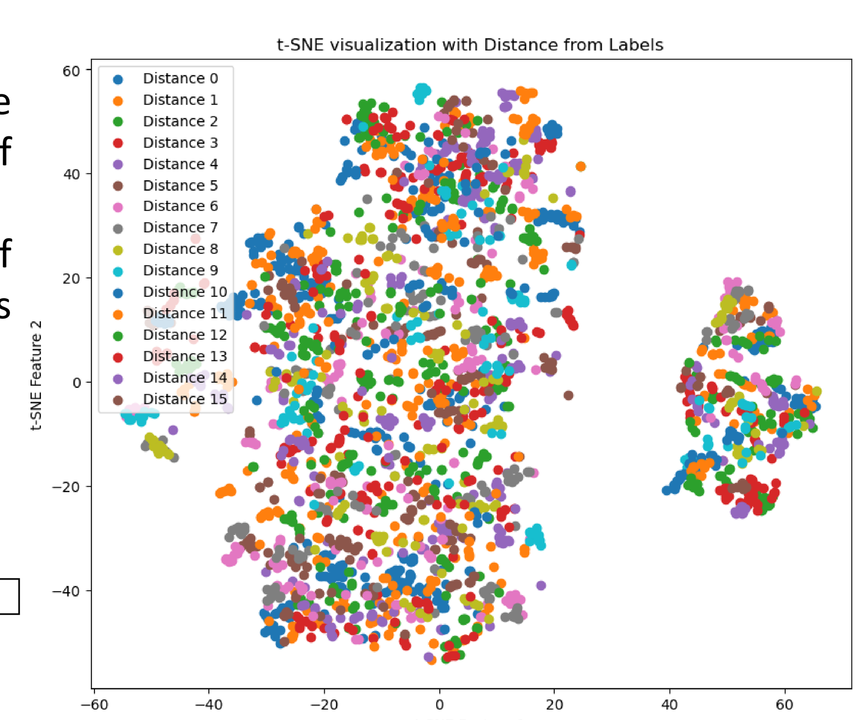
Confusion Matrix based on our validation data(RNN)





The **SVM** model is relatively more stable across different numbers of MFCC compared to the RNN model.
The **RNN** model shows a high degree of variability in performance metrics across different numbers of MFCC.

The clustering results reveal a random distribution of hits, indicating no clear clustering pattern based on the distance to the PIG.



Clustering for distance(K-means)

Conclusion

-We have identified that while SVMs provide relatively higher accuracy and recall in distinguishing between PIG and Non-PIG hits, the performance of both classifiers (SVM and RNN)can be significantly influenced by the choice of feature extraction methods, particularly the number of MFCC coefficients used, RNN is significant sensitive to it.
- Our models struggled with the more complex task of accurately classifying hits based on their distance from the PIG.
- This difficulty was further echoed in the k-means clustering attempts, which did not reveal any significant patterns.
- Incorporating more diverse acoustic features or combining audio data with other sensor data might improve model sensitivity to spatial variations and enhance distance-based classification accuracy.

Acknowledgements

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References (brief)

[1] Chowdhury, M. S., & Abdel-Hafez, M. F. (2016). *ASME J. Risk Uncert. Eng. Syst. B Mech. Eng.*, 2(2), 021001.
[2] Bernasconi, G., & Giunta, G. (2020). *Journal of Petroleum Science and Engineering*, 194, 107549.