PIPELINE INSPECTION GAUGE DETECTION USING PERCUSSION-BASED MACHINE LEARNING MODELING

MICHAEL ZAKARIA - UNDERGRADUATE
Department of Mechanical Engineering, Cullen College of Engineering

PROBLEM STATEMENT

This project aims to develop a non-invasive machine learning method for detecting Pipeline Inspection Gauges (PIGs) in closed pipelines. Continuous research is crucial for enhancing detection accuracy and efficiency, reducing the risk of pipeline failures. Tracking the PIG's location is vital to prevent disruptions and ensure pipeline integrity. An ML model facilitates prompt action to resolve any obstructions, minimizing downtime and failure risks.

BRIEF LITERATURE REVIEW

Currently, there is previous research that introduces passive tracking methods for Pipeline Inspection Gauges (PIGs) that utilize the gauge's own noise, eliminating the need for additional equipment. Three techniques are proposed, demonstrating effective applicability in real-world scenarios without requiring active systems. Some other research establish models to predict and control PIG velocity, crucial for optimal functioning. Using finite element method (FEM), various factors influencing PIG velocity are analyzed, and prediction models based on polynomial fitting, support vector machine (SVM), and neural networks are developed, with neural networks offering superior accuracy and wider applicability.

EXPERIMENTAL SETUP AND COLLECTION OF DATA

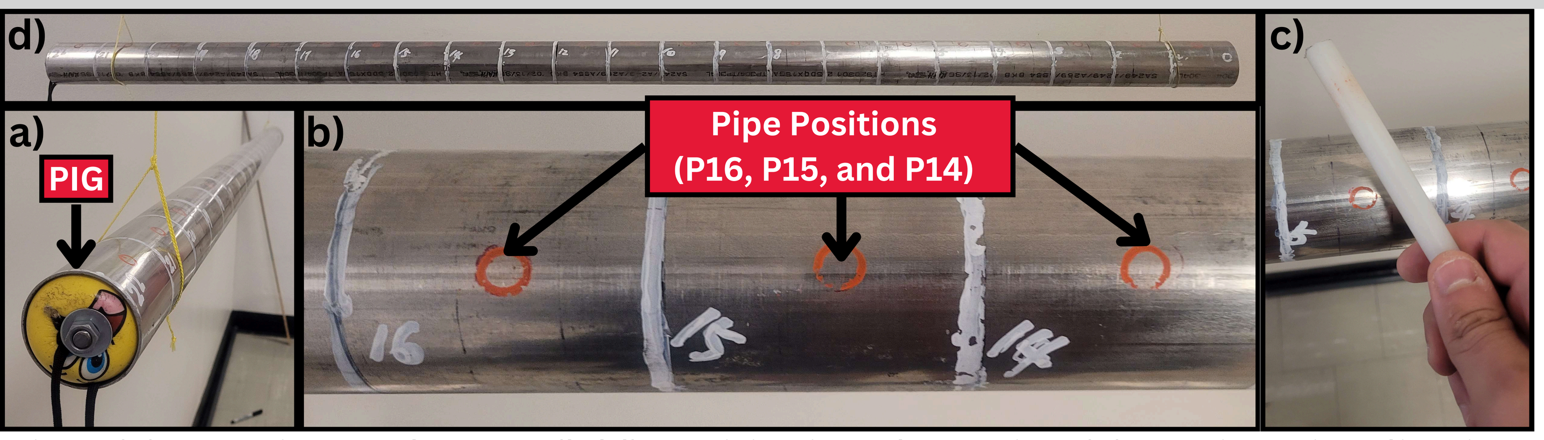


Fig 1. (a) Experimental Setup (b/d) Positioning along pipe (c) Testing Visualization

Fig 2. Single PIG Set Data Example at Position 4

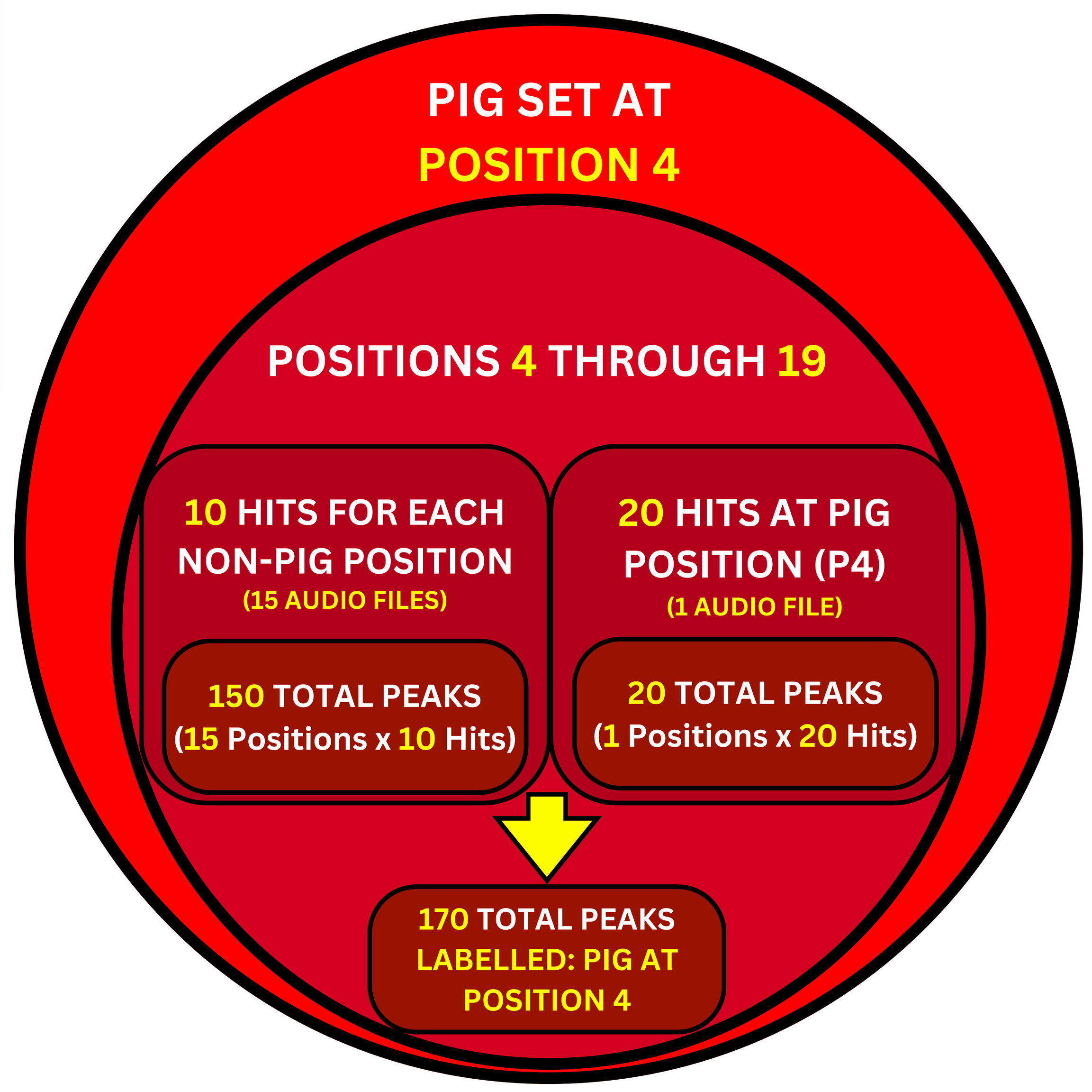


Fig 3. PIG Example Training Audio Peak Extraction

- The experimental setup comprises a steel pipe housing a PIG, with PIG adjustments facilitated by a ruler and rope to facilitate data collection at designated positions (as delineated in Figure 1. (b/d)).
- Data collection entails utilizing an audio recorder to capture sets of data for each PIG at various positions, as illustrated in Figures 2 and 3. Figure 3 showcases the extraction and labeling of peaks from each audio file. Notably, Figure 2 represents a dataset specific to one PIG instance, necessitating repetition for each alternative position aside from position 4.
- The data collection process encompasses multiple cases, with each case representing a distinct PIG position within the steel pipe. Data are organized and labeled systematically, with each dataset corresponding to a specific PIG position. Peaks within the audio files serve as key data points, allowing for comprehensive analysis and interpretation of the recorded data.

METHOD(S)

Signal Processing Method(s):

- Processing cut function for peak extraction.
- Mel-Frequency Cepstral Coefficients (MFCC) extraction for peak analysis. Spectral features like MFCCs effectively capture the distinctive frequency content and characteristics of peaks, enabling robust and efficient representation for analysis and classification purposes.

Preprocessed vs Processed:

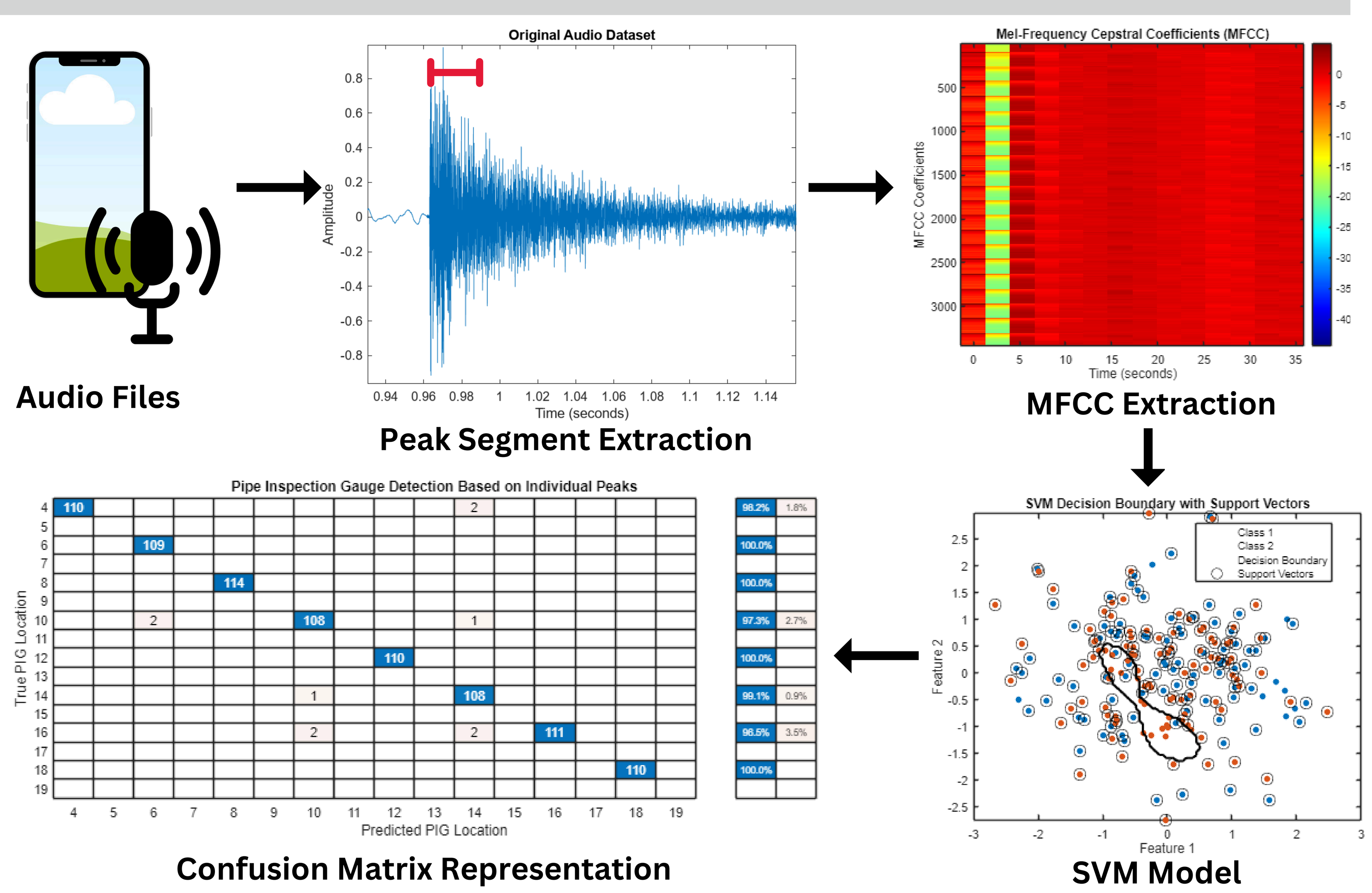
- Dimensionality reduction due to peak extraction.
- MFCC extraction condenses data while preserving relevant features.

Classification Method:

- Support Vector Machine (SVM) modeling was used with the MFCC processed data as it provided the most consistent PIG classifications.

Innovation:

- For each audio file, all the peaks were classified under the PIG location. As displayed in Figure 3, there was a summation of 170 total peaks categorized as the PIG being at position 4.



RESULTS, ANALYSIS, AND DISCUSSION

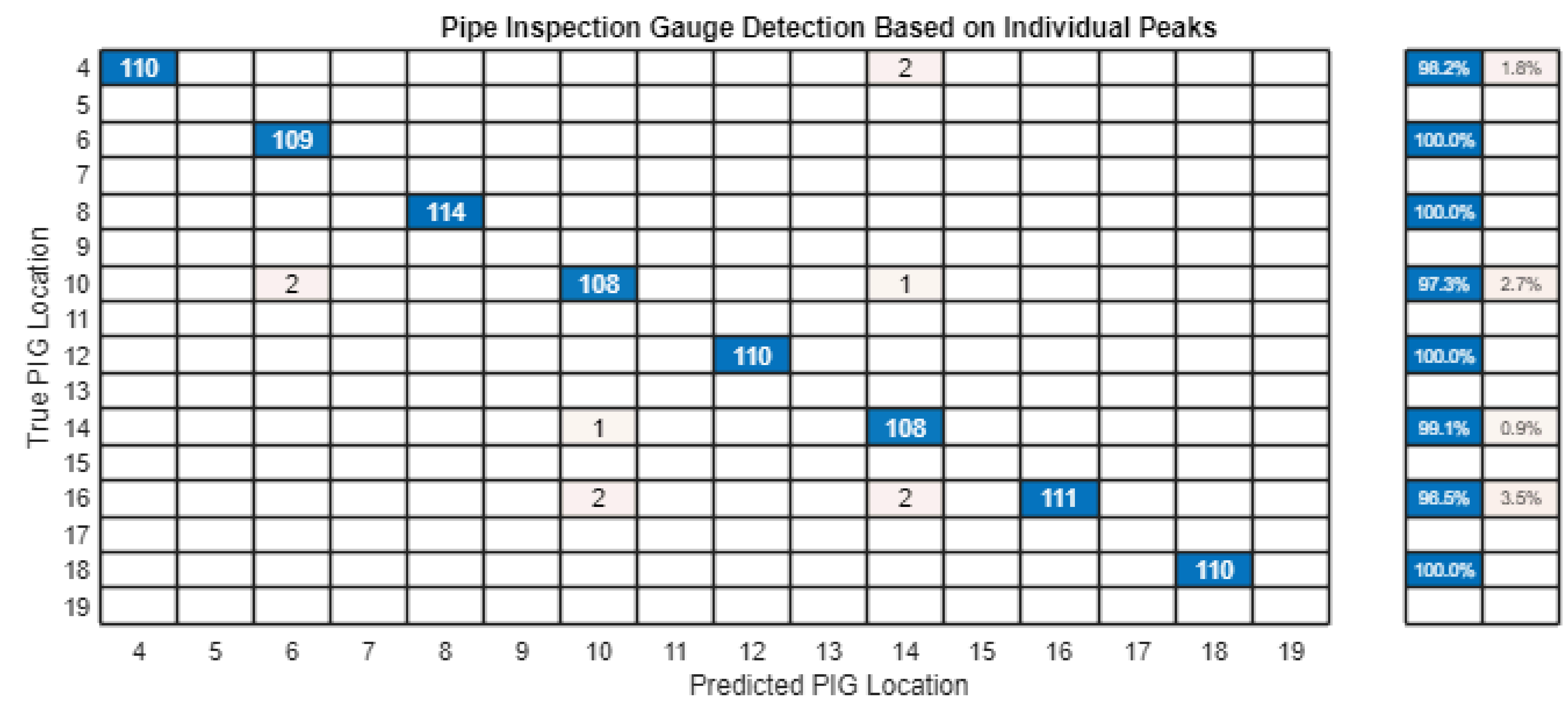


Fig 4. Confusion Matrix for PIG Detection Based on Individual Peaks for Test Set 1

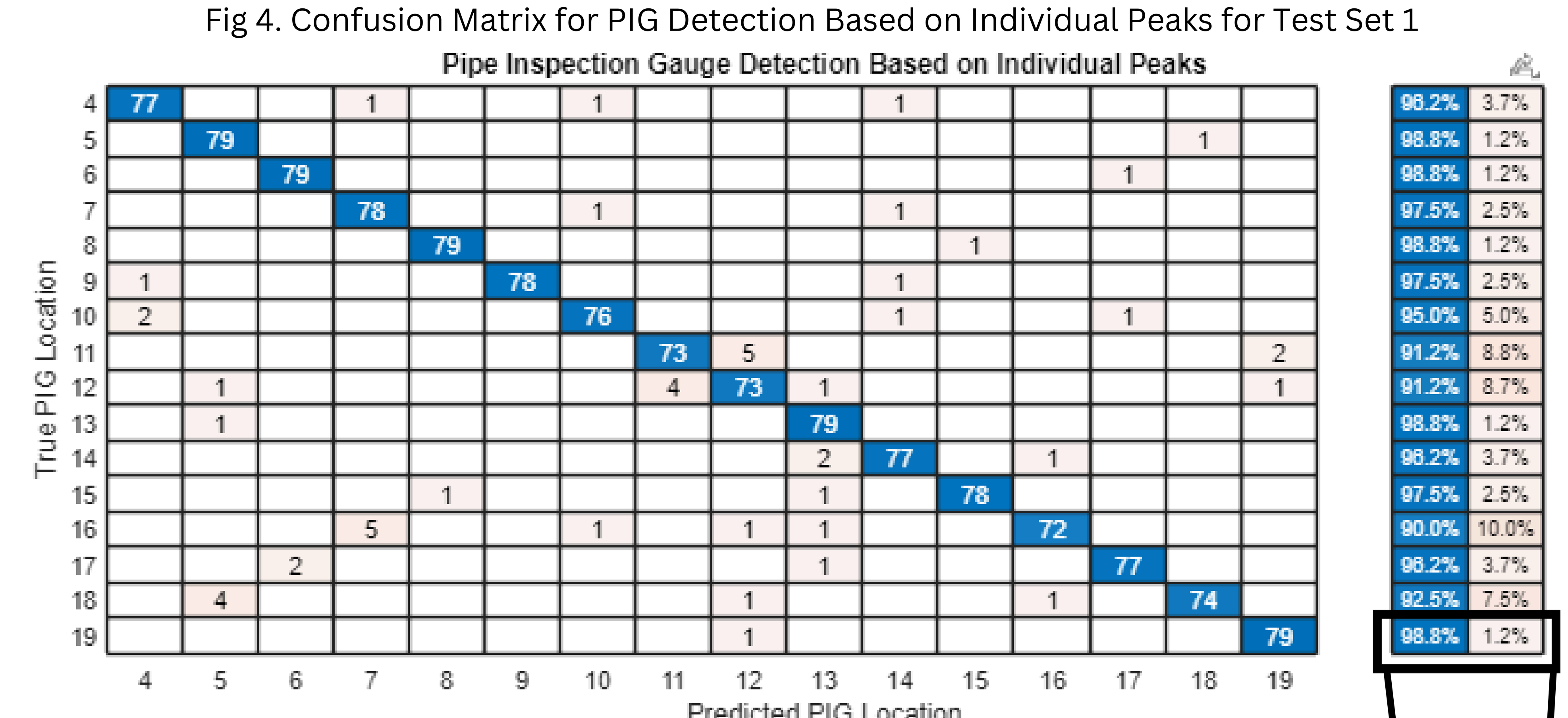


Fig 5. Confusion Matrix for PIG Detection Based on Individual Peaks for Test Set 2

This indicates that based on the peaks used to train the SVM model, it was able to predict that the PIG was located at position 19 with 98.8% accuracy and 1.2% inaccuracy, (79 Correct, 1 Incorrect) | 98.8% | 1.2%

- **In Figure 4 and 5, the prediction of the processed peaks extracted from both testing sets were tested using SVM and plotted onto a confusion matrix.**
- **Based on the results of the confusion matrix, the average accuracy for the detection of each PIG was 97%, proving the consistency of determination from the model.**

CONCLUSION

- **Instead of labeling each audio file, each peak within the audio file was labeled instead. This provided better results when run through the SVM model, yielding an accuracy of 97%.**
- **Further experimentation may include potentially solving and utilizing the damping ratio for each peak and using that data rather than the peaks. For this to happen, a filter must be applied for better quality data.**
- **Pipeline inspection gauge (PIG) detection is critical for ensuring the integrity and safety of pipelines. Continuous research in this field is essential to enhance detection accuracy and efficiency, thereby minimizing the risk of pipeline failures and associated environmental and economic consequences.**

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.

REFERENCES

1. Yang, Y., Zhang, Z.-M., Jia, Y.-R., Zhang, K., & Gong, Y.-J. (2024). Research and prediction of pipeline inspection gauges velocity based on simulation and neural network. Measurement, 224, 113847. https://doi.org/10.1016/j.measurement.2023.113847
2. Bernasconi, G., & Giunta, G. (2020). Acoustic detection and tracking of a pipeline inspection gauge. Journal of Petroleum Science and Engineering, 194, 107549. https://doi.org/10.1016/j.petrol.2020.107549