Project Title: Machine Learning-Enhanced System for Detecting of Lost Pipeline Inspection Gauge (PIG)

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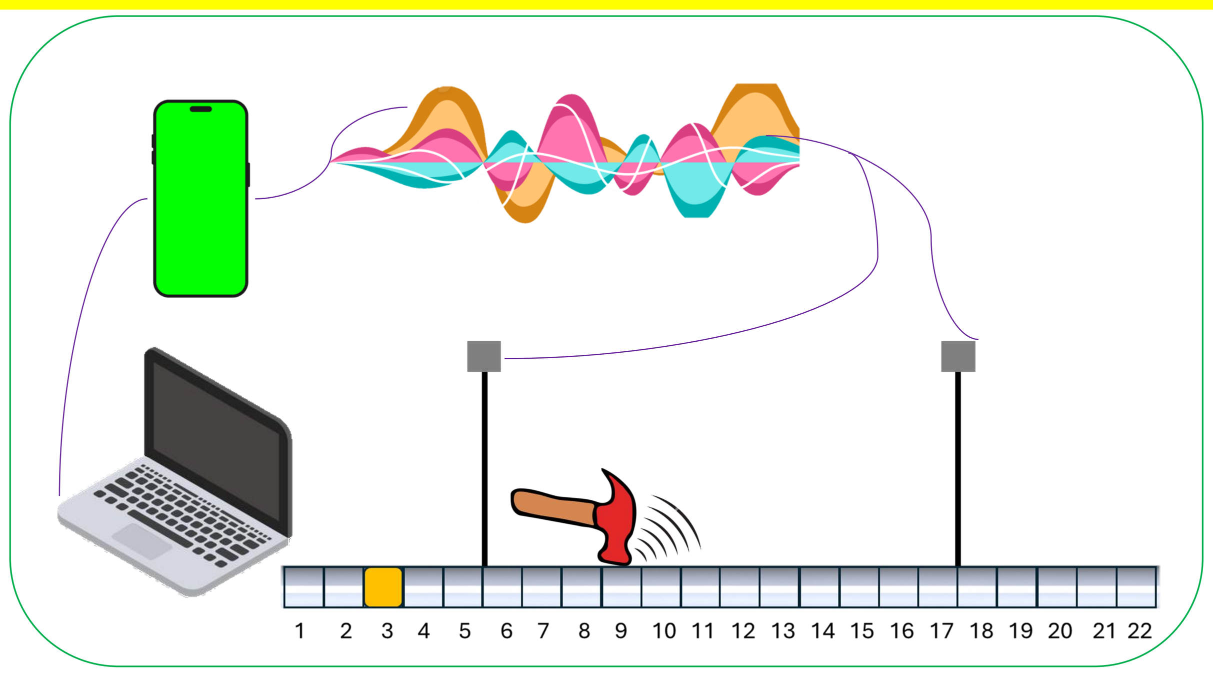
Problem Statement

Pipeline inspection gauges (PIGs) are vital for pipeline maintenance, performing tasks like cleaning and assessing pipe conditions. Types include cleaning, batch, and smart pigs. Challenges like pipeline bends or deposits can hinder PIG movement, potentially causing disruptions and financial losses. Monitoring strategies, including surface-based percussion sounds, are used to detect and predict PIG locations effectively.

Brief Literature Review

Large standoff magnetometry (LSM) technology can detect changes in magnetic fields around the pipeline, which helps to identify the stuck PIGs or obstructions even from a significant distance[1]. However, use of percussion-based sound to detect pigs is a cost-effective approach. J. chen used a novel approach, the Feature-reduced Multiple Random Convolution Kernel Transform (FM-ROCKET), for detecting bolt looseness in underwater environments using percussion-induced sound signals[2].

Experimental Setup and Collection of Data

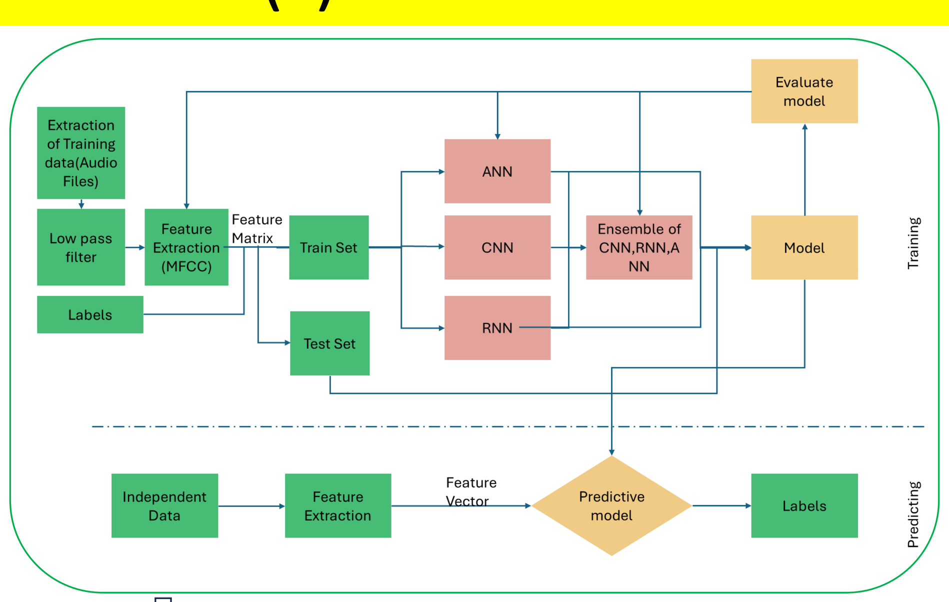


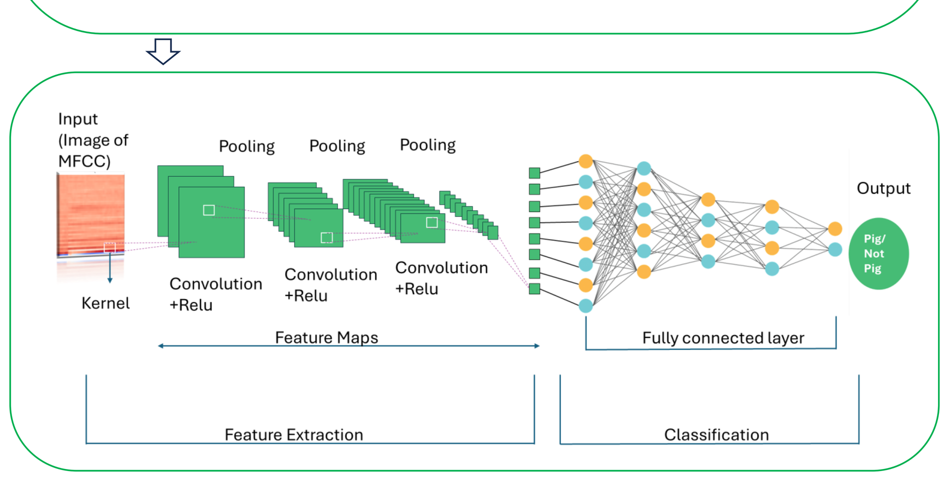
Data Naming Convention: Files were systematically named starting from 1-1, 1-2, etc., indicating the foam pig's position within segment 1 of the steel pipe, aiding in data organization and identification.

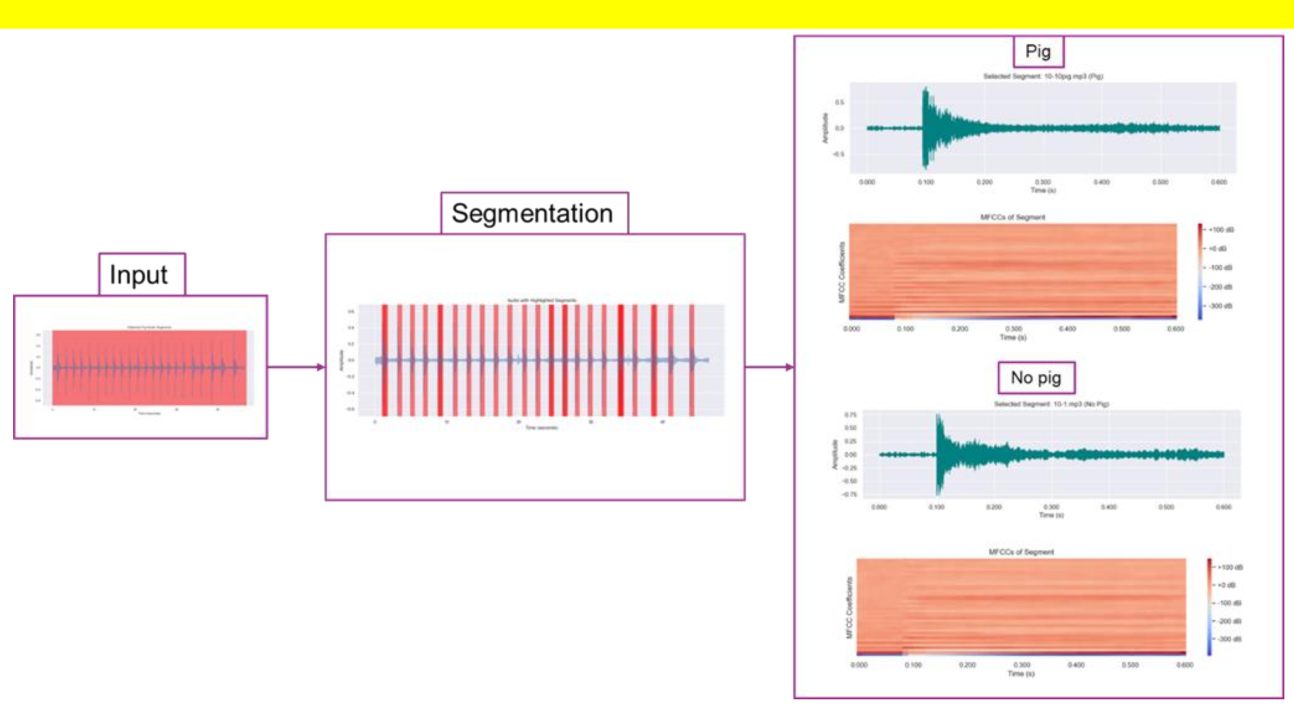
Experimental Procedure: The foam pig was moved across segments 4 to 20 of the pipe. Impacts were made along the pipe to capture the acoustic signature: 10 strikes in pig-absent segments, 40 in pig-present segments, and 20 in adjacent segments.

Striking Protocol: A consistent striking protocol was applied to each segment, ensuring a comprehensive dataset that documented the acoustic responses due to the pig's presence, absence, and proximity.

Method(s)



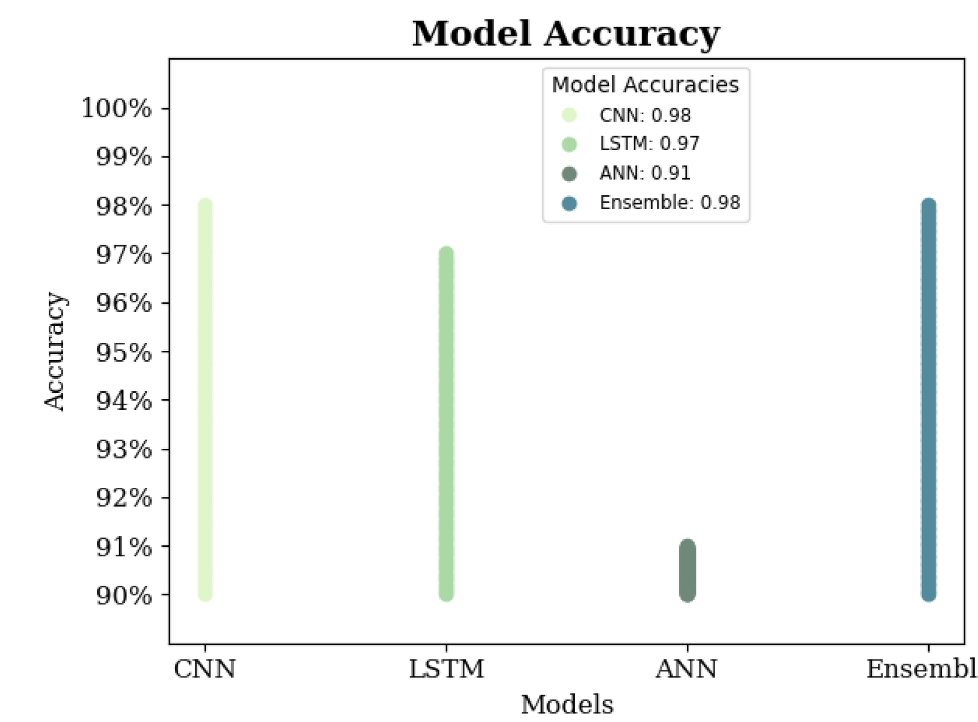


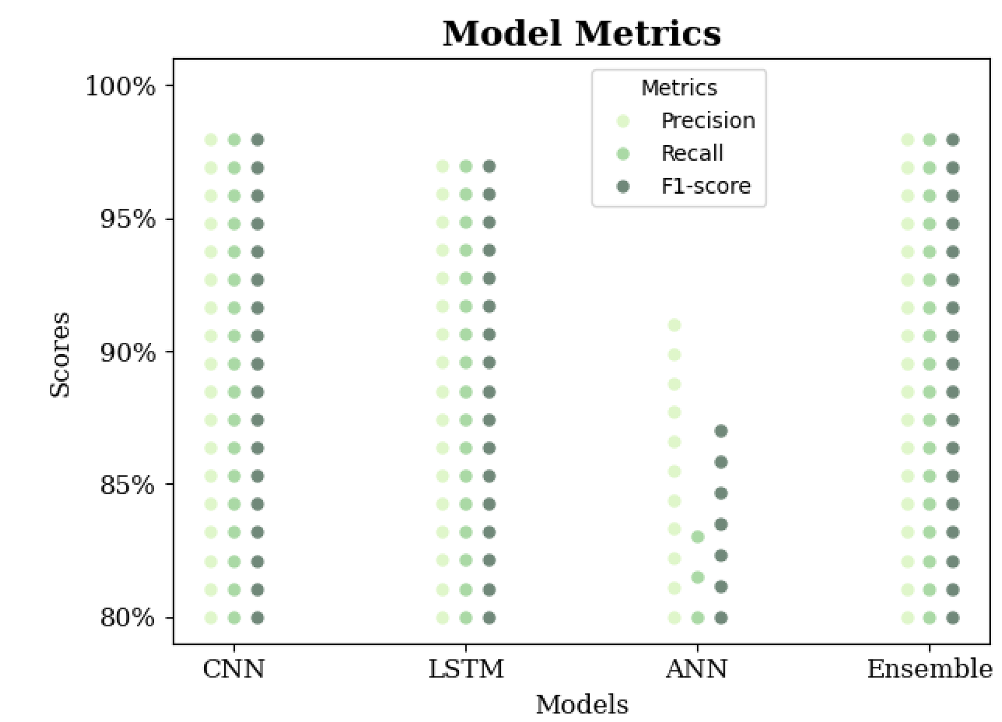


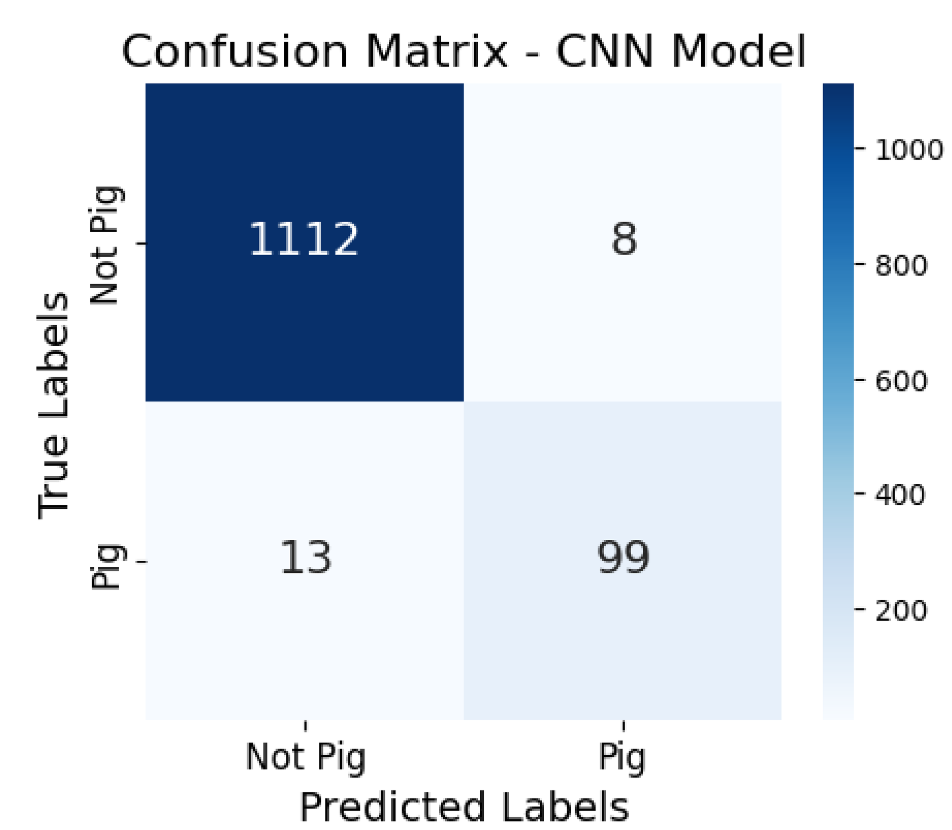
Data Preparation and Feature Extraction: Training data (audio files) are first processed with a low pass filter, followed by feature extraction where Mel Frequency Cepstral Coefficients (MFCC) are derived to form a feature matrix. This matrix is then split into training and test datasets, with corresponding labels.

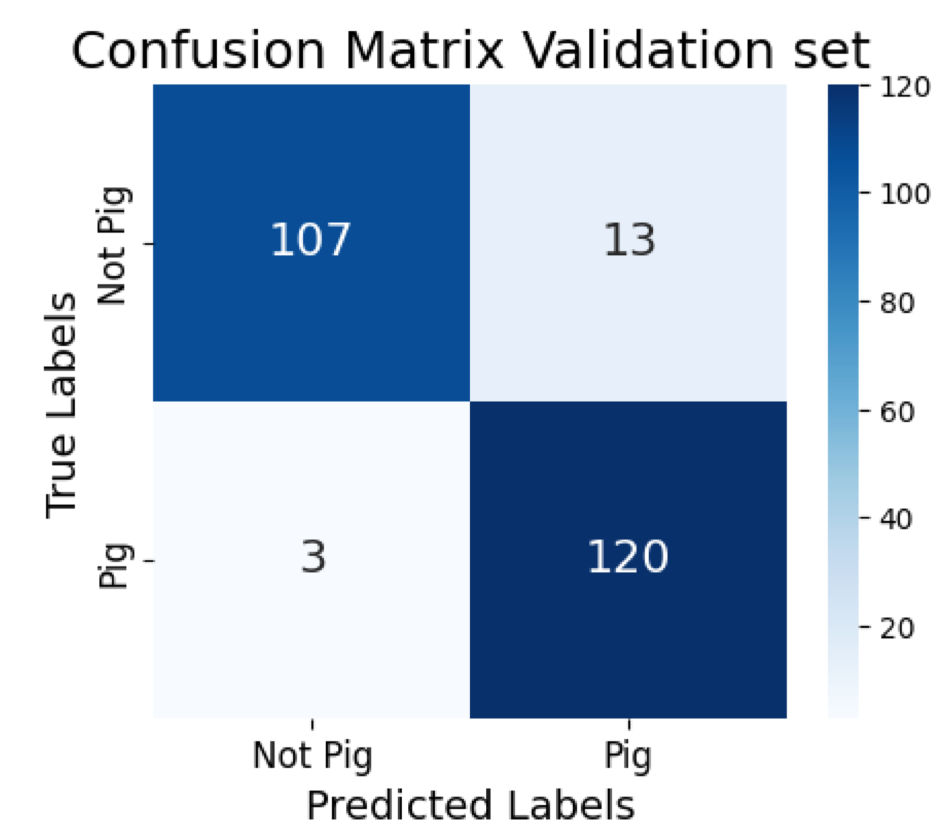
Model Training: The training set is used to train three types of neural networks—Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) These models are then combined into an ensemble to leverage the strengths of each model type for improved performance.

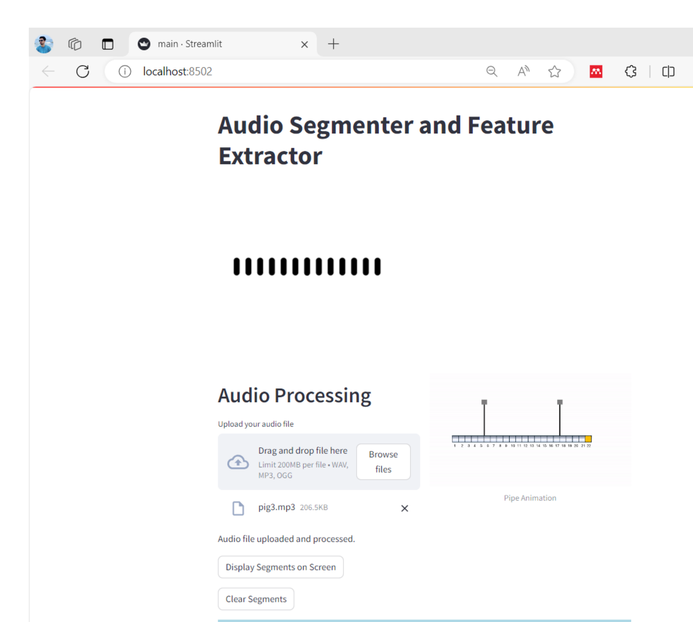
Results, Analysis and Discussion











- Evaluation metrics and charts show model performance, highlighting precision-recall trade-offs. Ensemble methods often outperform individual models, though limitations may arise from individual weaknesses or systematic errors.
- All models in the outputs display high performance, with the ensemble slightly leading in accuracy. Precision, recall, and F1-score indicate well-tuned models, with minor variations possibly due to generalization differences.

Conclusion

In conclusion our experiments, supported by a methodical data collection process and meticulous feature extraction, have paved the way for advanced pipeline monitoring. The data, segmented around key acoustic events and enriched with MFCC features, provided a solid foundation for the models to learn and make accurate predictions. .The models' ability to distinguish between "pig" and "not pig" sounds with such precision underscores the power of neural networks in auditory data analysis.

Acknowledgements

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References (brief)

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2. J. Chen, Z. Chen, W. Zhu, and G. Song, "Underwater bolted flange looseness detection using percussion-induced sound and Feature-reduced Multi-ROCKET model," Struct Health Monit, vol. 23, no. 1, pp. 495–511, Jan. 2024, doi: 10.1177/14759217231153991/ASSET/IMAGES/LARGE/10.1177_14759217231153991-FIG12.JPEG
3. F. Wang, S. C. M. Ho, and G. Song, "Modeling and analysis of an impact-acoustic method for bolt looseness identification," Mech Syst Signal Process, vol. 133, p. 106249, Nov. 2019, doi: 10.1016/J.YMSSP.2019.106249