Project Title: Real-time Pig Location Detection Using Acoustic Signals

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Problem Statement

- The steel composition of above-ground oil and gas pipelines obstructs signal transmission from Pipeline Inspection Gauges (PIGs), restricting traditional methods for locating lost PIGs.
- This project aims to develop a real-time system using acoustic signals and Arduino boards to detect and retrieve lost Pipeline Inspection Gauges (PIGs) in above-ground oil and gas pipelines. Acoustic signals are chosen because PIGs dampen these signals due to their sponge-like material, aiding in distinguishing them from other sections of the pipeline where the PIG is not present. The process can be automated using a robot for streamlined maintenance and inspection.

Brief Literature Review

- Conventional methods for tracking Pipeline Inspection Gauges (PIGs) include acoustic pingers or electromagnetic emitters, which communicate with receivers to determine their position, and dense sensor networks [1]. Another state-of-the-art method involves employing data-driven techniques to estimate the location of stuck PIGs [2].

Experimental Setup, Collection of Data, and Innovation.

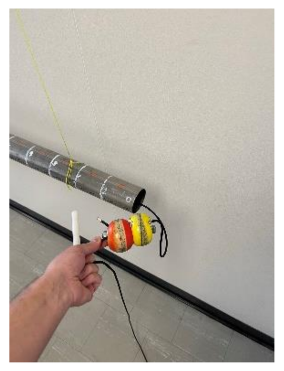


Figure 1. PIG

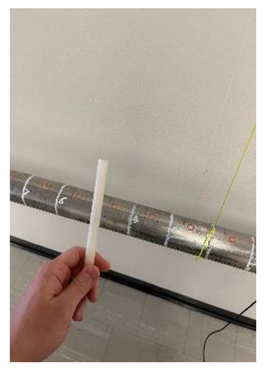


Figure 2. Round Stick

Figure 3. Wooden Ruler

Figure 4. Pipe

1. **304L Stainless Steel Pipe**
   - Length: 66 inches
   - Diameter: 2.5 inches
   - Wall Thickness: 16 gauge
   - Suspension: Two ropes from ceiling
   - Markings: Every 3 inches, 22 sections total
   - Reference: Figure 4
2. **Wooden Ruler**
   - Length: 39 inches
   - Purpose: Measure PIG's location
   - Reference: Figure 3
3. **White Round Stick**
   - Purpose: Used like a hammer to strike the pipe
   - Reference: Figure 2
4. **Sponge Ball PIG**
   - Description: Two sponge balls joined, forming a 3-inch PIG
   - Connection: Two ropes for positioning inside the pipe
   - Reference: Figure 1

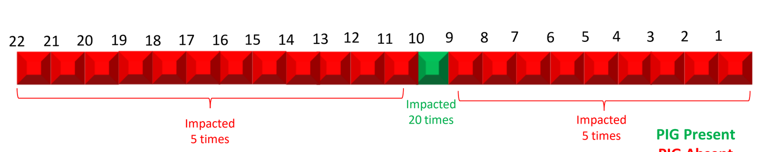
Data Collection Devices:

5. **iPhone**
   - Function: Record sound data

Data Collection:

- **Training Data:** The PIG was positioned at grids 1 to 19. At each position, the grid was impacted 20 times. For grids without a PIG, the impact was repeated 5 times. This process was repeated for each grid where the PIG was positioned.
- Total training audio files: 418
- Total impacts: 2375
- Impacts where the PIG was present: 380
- Impacts where the PIG was absent: 1995

- **Testing Data:** The PIG was initially positioned at grid 1, and each grid from 1 to 19 was impacted 5 times. Subsequently, the PIG was moved to grid 2, and the process was repeated for each grid from 1 to 19. This pattern continued until the PIG reached grid 19.
- Total testing audio files: 19
- Total impacts: 1805
- Impacts where the PIG was present: 95
- Impacts where the PIG was absent: 1710



Real-time Pig Location Detection using Acoustic Signals and Adreno Board Integration

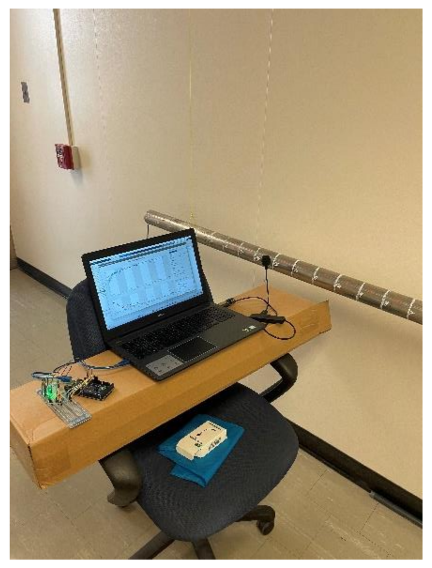


Figure 5. Real-time Pig Location Detection Setup

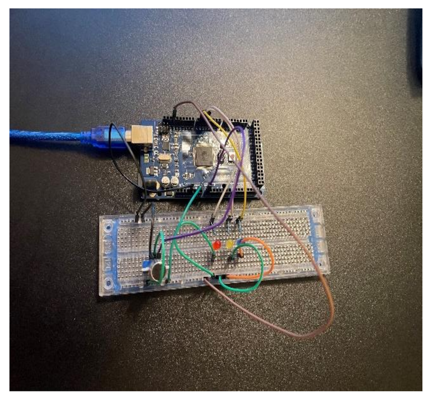


Figure 6. Arduino mega 2560 Board Setup

1. USB Microphone
- Function: Collect live data
- Reference: Figure 5

2. Arduino Mega 2560 Board
- Function: Control LED indication lights
- Reference: Figure 6

3. Breadboard
- Function: Component mounting
- Reference: Figure 6

4. Jumper Wires
- Function: Connect components on breadboard
- Reference: Figure 6

6. Resistors
- Function: Electrical resistance in circuit
- Reference: Figure 6

7. LED Light
- Function: Visual indication
- Color Code:
- Blue: PIG present
- Yellow: Error
- Red: No PIG
- Reference: Figure 6

8. Laptop
- Purpose: Data processing and model creation
- Reference: Figure 5

This approach encapsulates real-time pig location detection via acoustic signals, harmonizing with Arduino board integration for LED feedback. It encompasses audio recording, MFCC processing, CNN label prediction, and LED signaling for detected pig locations. This method denotes blue for pig presence, yellow for error, and red for no pig detected.

Method

Data Segmentation:

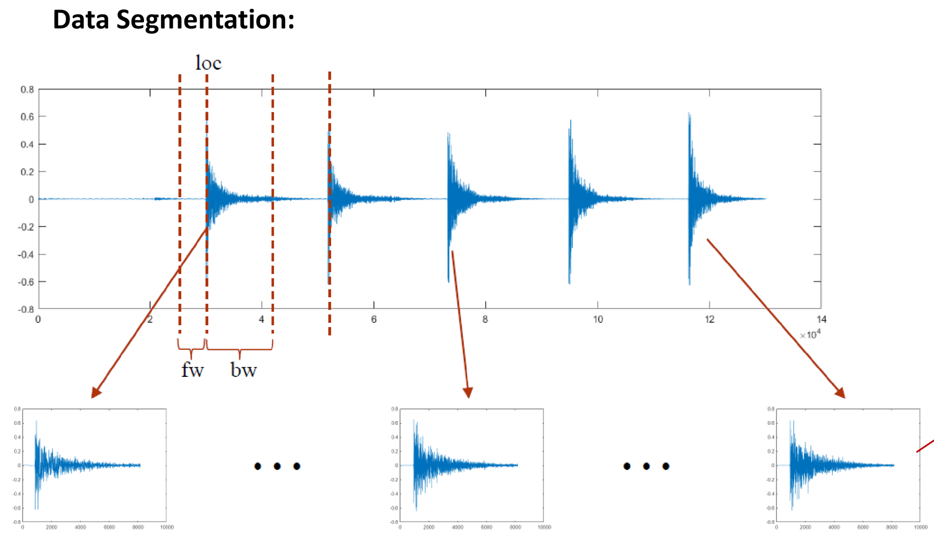


Figure 7. Data Segmentation [4].

Signal Processing (MFCC):

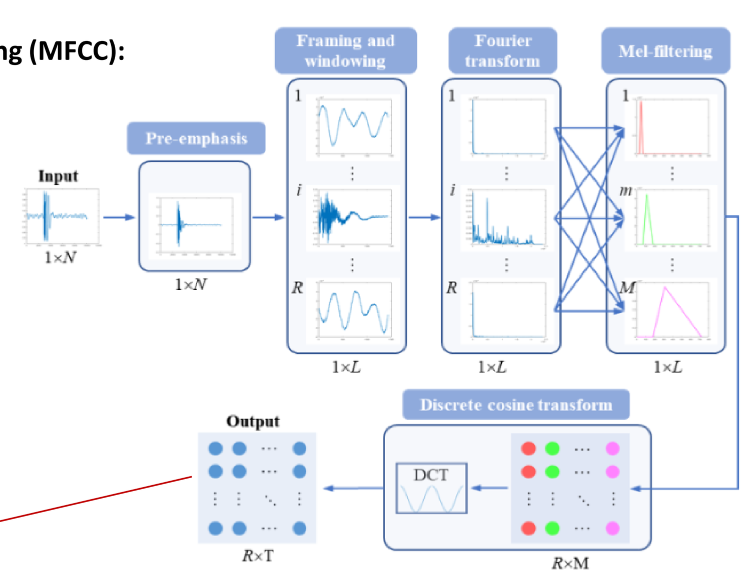


Figure 8. Outline of MFCC [4].

Training and Classification Method (CNN):

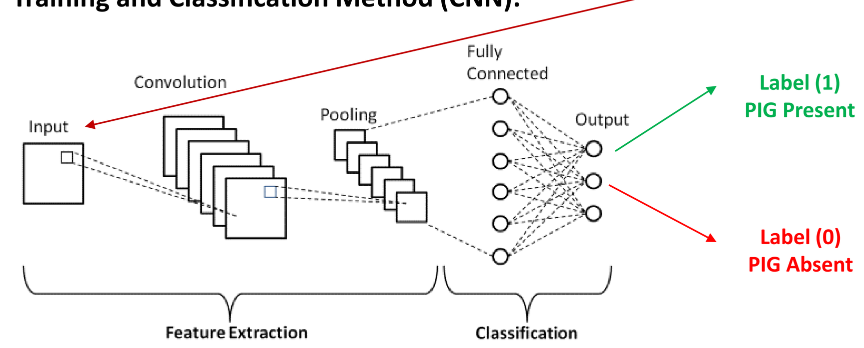


Figure 9. Outline of CNN [3].

Convolutional Neural Networks (CNNs): are deep learning models tailored for tasks like image processing. They consist of layers: input (receives data), convolutional (extracts features), ReLU (adds non-linearity), pooling (reduces dimensions), and full connection (implements classification). CNNs excel at learning hierarchical representations of input data, particularly in image recognition and classification [5].

Mel-frequency cepstral coefficients (MFCC): represent the short-term power spectrum of an audio signal [4]. Figure 8 provides a visual aid to understand the process of MFCC extraction.

Results, Analysis and Discussion

Labels (1,0) PIG Present, PIG Absent

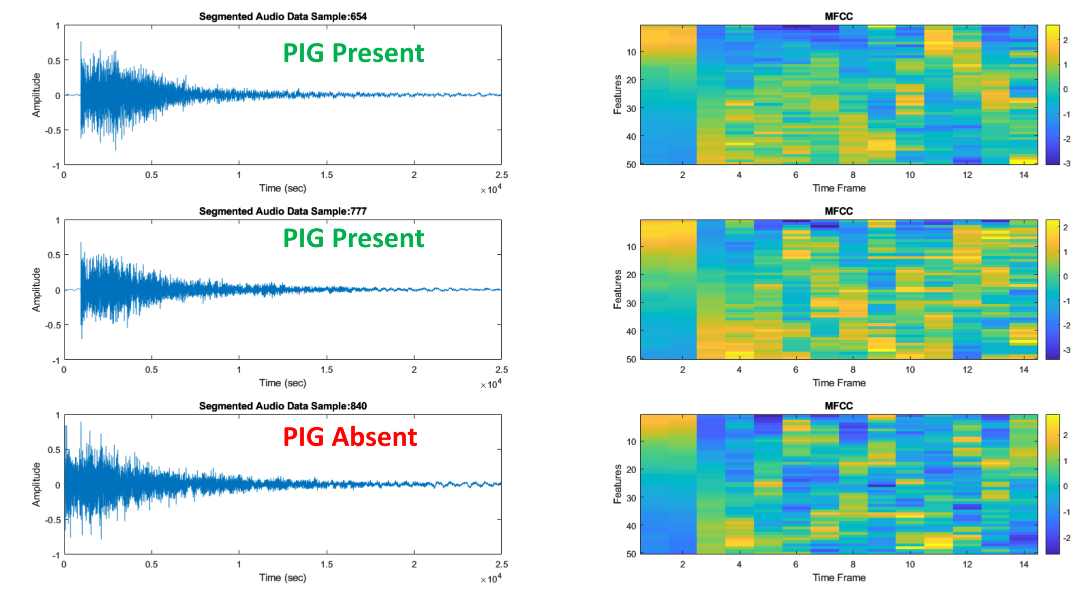


Figure 10: Raw Segmented Audio and Corresponding MFCC Representation

Labels (1-19,0) PIG Present, PIG Absent

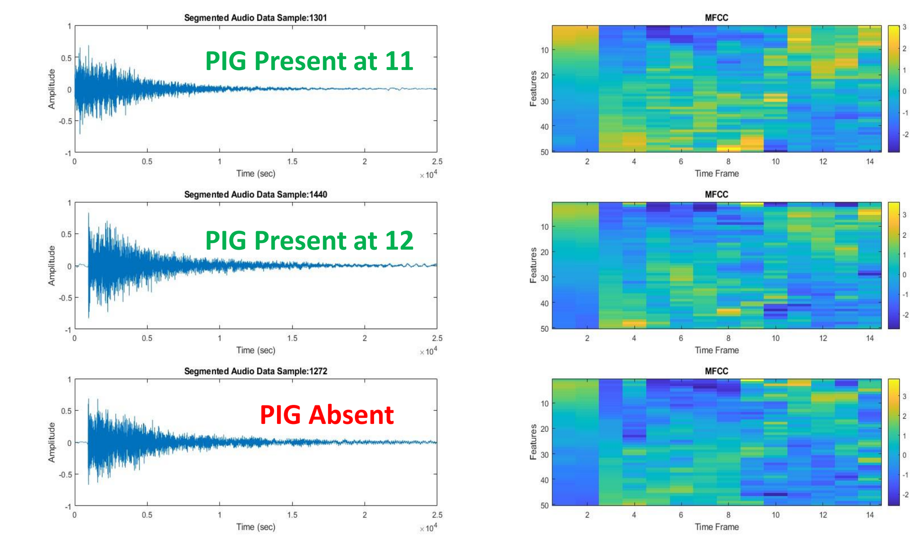


Figure 11: Raw Segmented Audio and Corresponding MFCC Representation

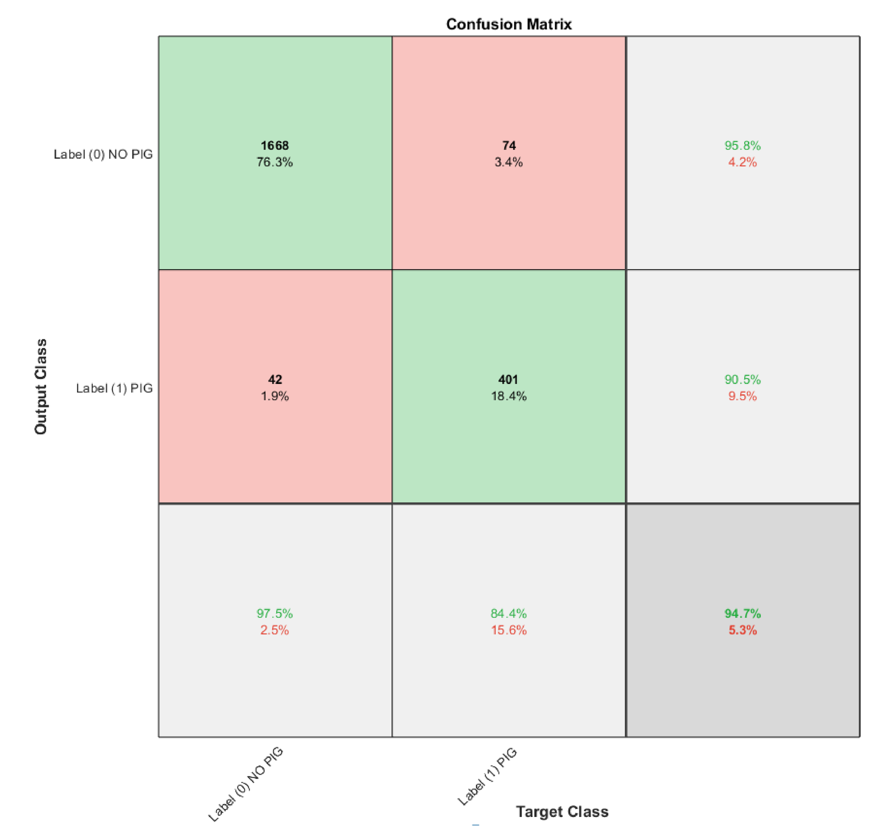


Figure 12: Confusion Matrix for Binary Classification (Labels: 0 - No PIG, 1 - PIG)

Accuracy: 94.7%

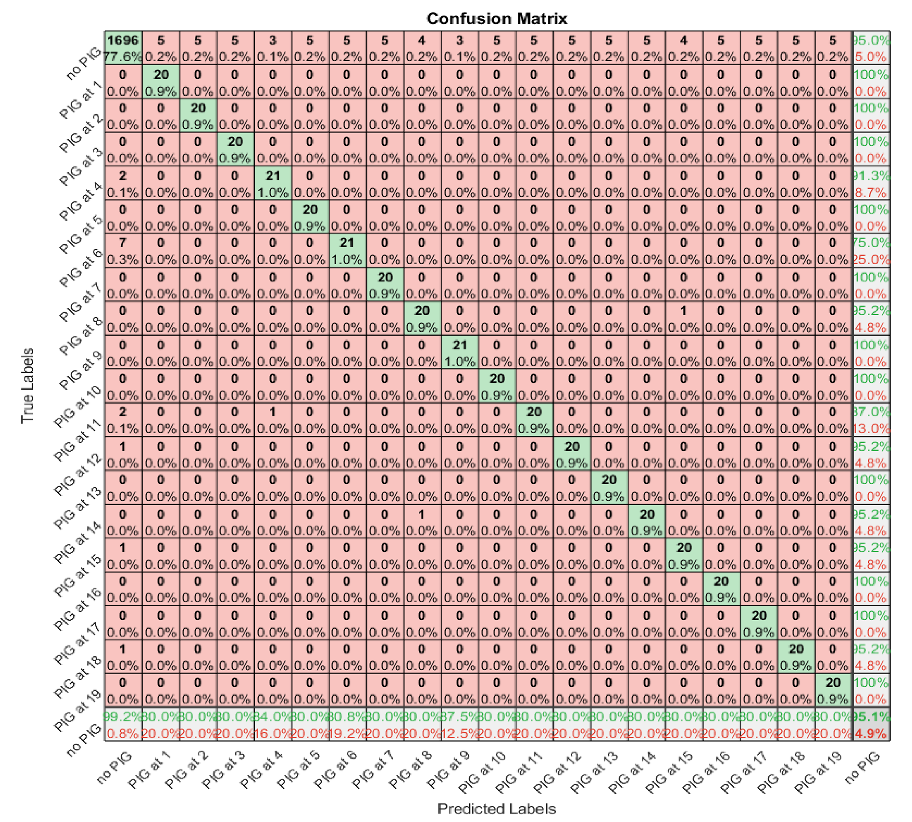


Figure 13: Confusion Matrix for PIG Classification (Labels: 1 to 19 for PIG, 0 for No PIG)

Accuracy: 95.1%

Discussion & Analysis : The CNN model achieved an accuracy of 95.1%, indicating strong performance in classifying PIG locations. Visualizations of MFCC data and raw audio samples provide insights into the features used for classification. The confusion matrix reveals an imbalance between PIG and NO PIG data, prompting the addition of more PIG data to enhance model performance. This augmentation is expected to improve accuracy, as MFCC fits well with CNN due to its transformation into image matrices, which CNN excels at classifying.

Conclusion

- **Case 1:** Classification Model

The fusion of Convolutional Neural Networks (CNN) with Mel-Frequency Cepstral Coefficients (MFCC) achieves a remarkable 95.1% accuracy in classifying Pipeline Inspection Gauges (PIG). Visualizations of MFCC data and raw audio samples enhance model understanding. The confusion matrix highlights data imbalances, guiding future augmentation efforts for improved performance.

- **Case 2:** Real-Time Deduction and Automation

While the system is not currently integrated with robots, the potential for future integration is promising. Automation of real-time PIG detection and inspection using robotic systems represents an exciting avenue for exploration. Enhancements such as improved microphone quality and seamless integration with robotic platforms could significantly advance the capabilities of the system for field deployment. Further research and development are needed to realize this vision.

Acknowledgements

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References

1. 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

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4. Class Notes

5. Balaji, S. (2023, August 26). Binary Image classifier CNN using TensorFlow - Sai Balaji - Medium. Medium. https://jokerpt.medium.com/binary-image-classifier-cnn-using-tensorflow-a3f5d6746697