Project Title: A Percussion-Powered Audio Classification Technique with Multiple Input CNN to Pinpoint Location of Pipe Inspection Gauge (PIG) in Steel Pipes

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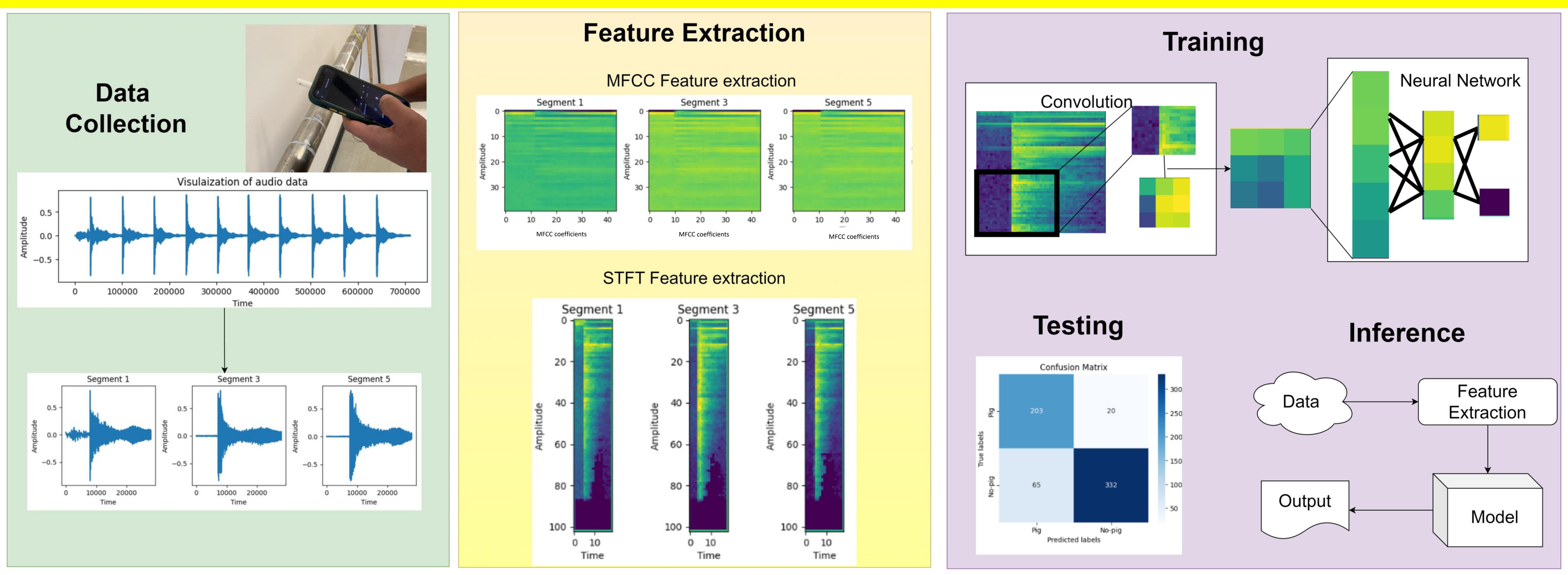
Problem Statement

Traditional methods for locating stuck or lost pigs in pipelines often rely on costly equipment and sophisticated sensors. An alternative method of percussion analysis is proposed in this project to find lost pig. Acoustic signals produced by percussion is recorded with a smart-phone and trained through machine learning can accurately identify location lost and can be cost effective as well.

Brief Literature Review

Percussion-based machine learning techniques are emerging as powerful and cost-effective method. Researchers have demonstrated their effectiveness in areas such as estimating bolt looseness, detecting sediment deposition in pipelines, identifying subsurface voids in concrete structures, and measuring moisture level form sound collected from percussion.

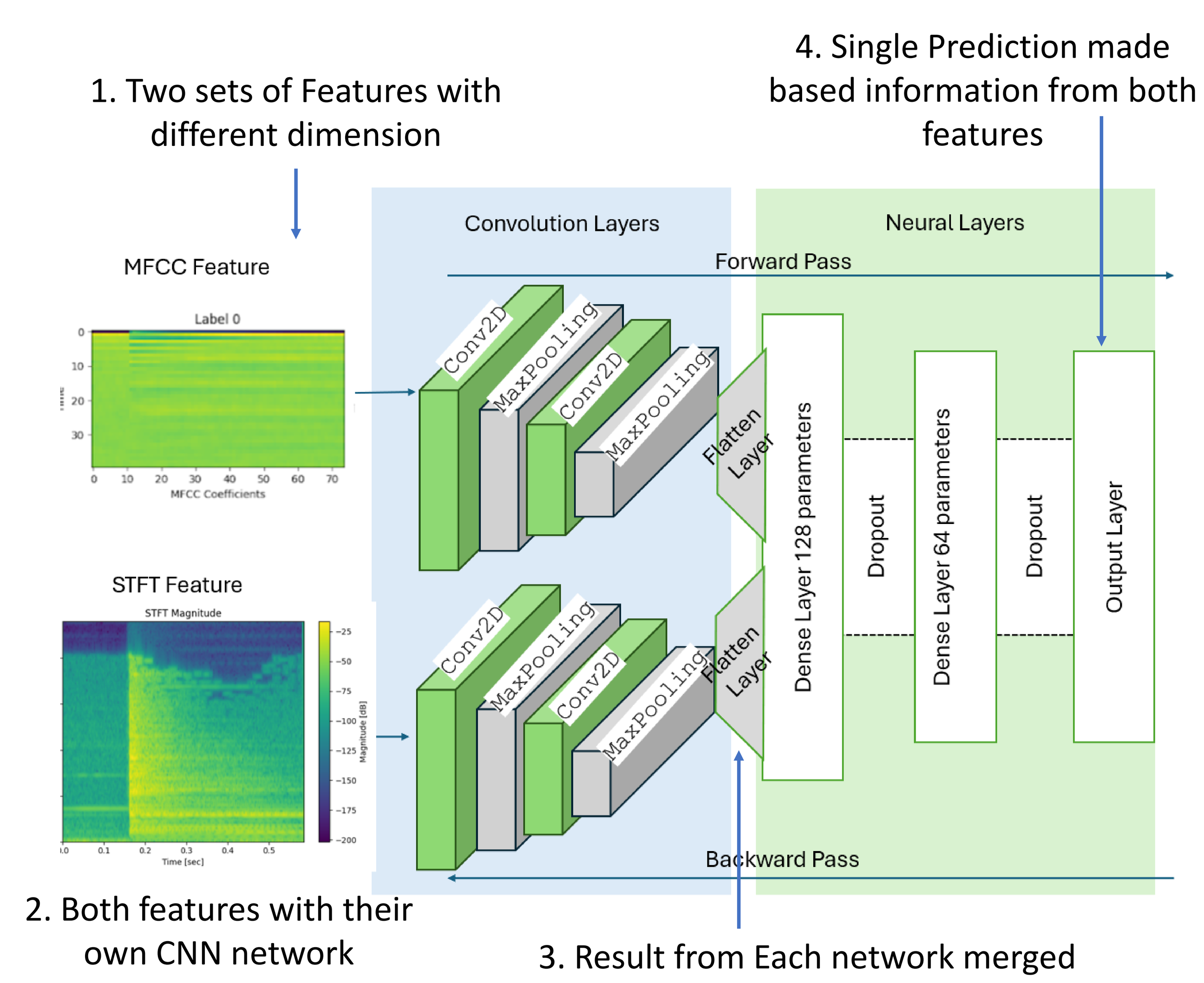
Experimental Setup and Collection of Data



- Data acquisition involves segmenting a metal pipe into 22 sections. Percussion is conducted at designated points within these sections, and recordings are captured using a smartphone.
- Collected sound of multiple percussion is divvied into induvial segments.
- Mel-Frequency Cepstral Coefficients(MFCC) and Short Time Fourier Transfer(STFT) methods were used for feature extraction as they are established techniques.
- The data was divided into training and testing sets for model optimization and validation. An additional independent dataset was created for verifying the real-world performance of machine learning model.

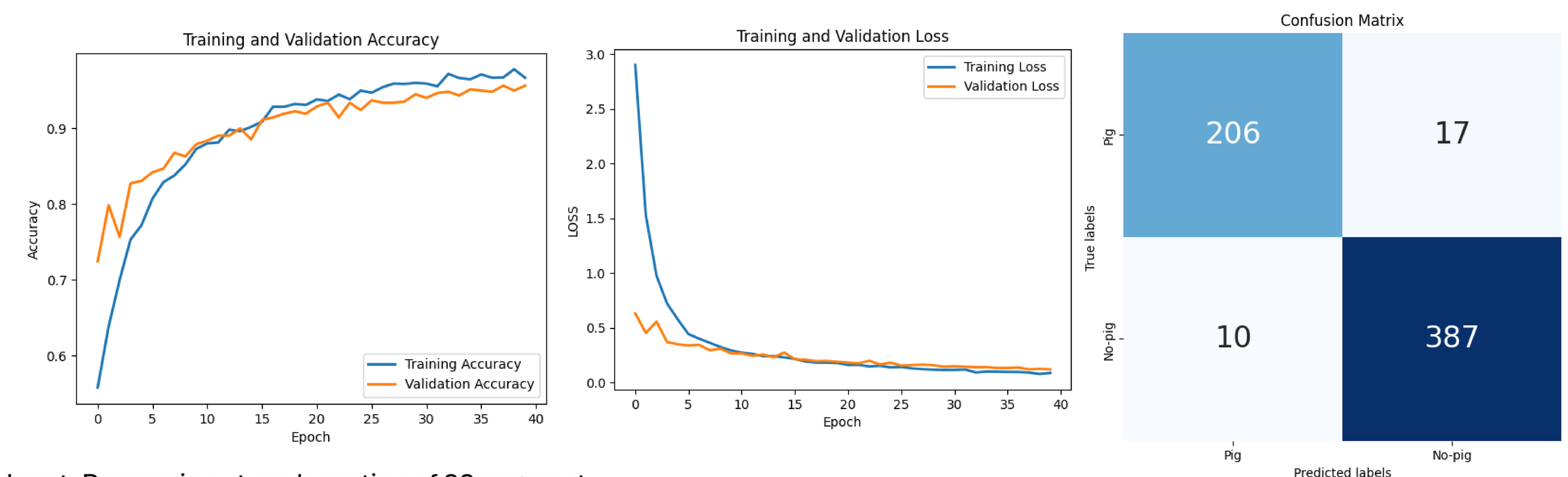
Method(s)

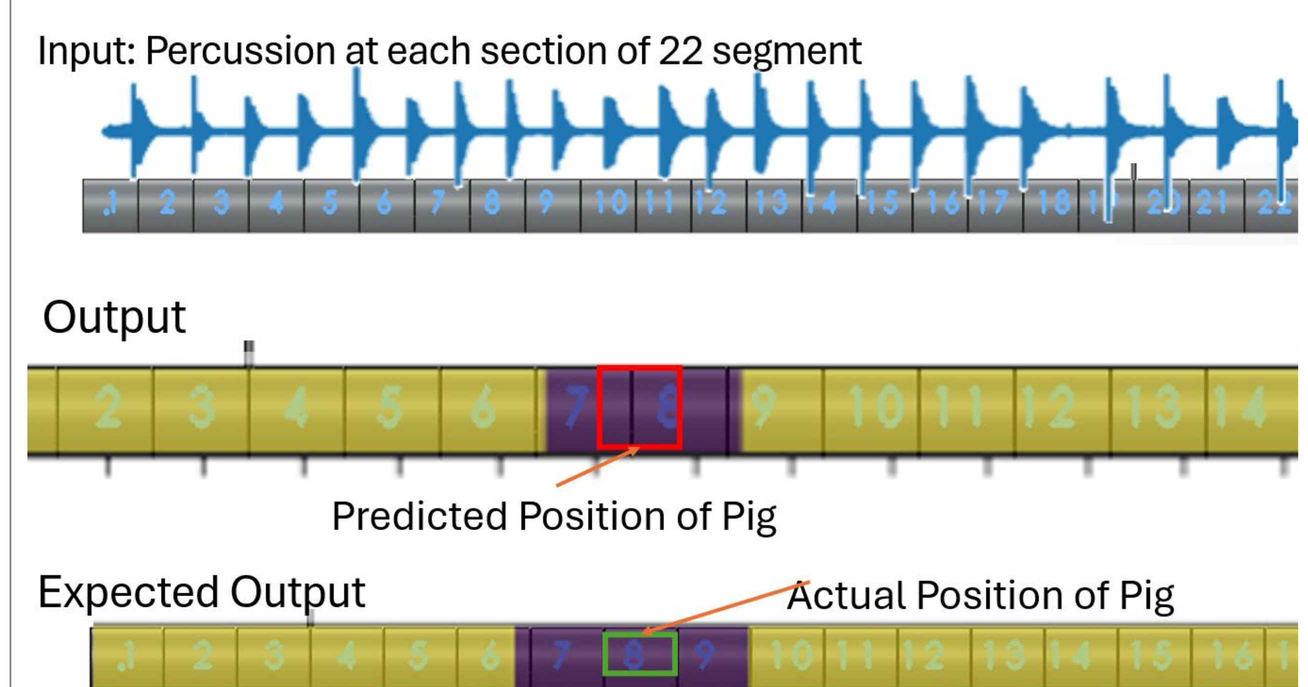
- **Multiple Input CNN architecture** for audio classification was used; leveraging separate pathways for temporal-spatial-spectral (STFT) and spectral features extraction (MFCC).
- Integration of outputs from independent feature pathways ensures diverse information extraction
- Multi Input CNN architecture can transcend limitations single-path CNNs, leading to higher classification accuracy and deeper understanding in audio analysis tasks.



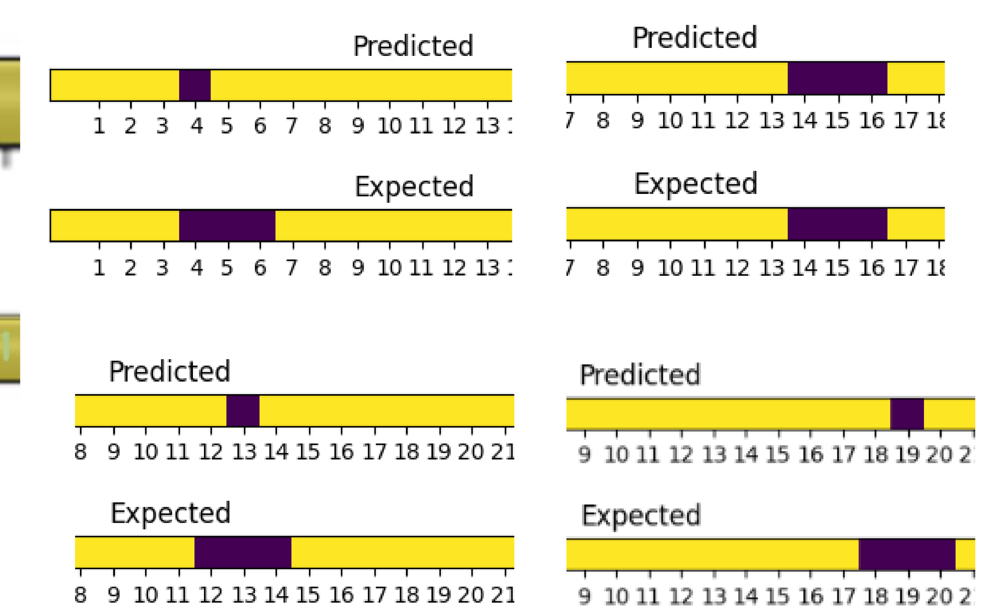
Results, Analysis and Discussion

- The model was trained for 40 Epochs, where the training and validation loss decreased as model parameters were optimized and the accuracy increased. The model was able achieve 95% validation accuracy at the end of training.
- The F1-score of "Pig" and "No Pig" classes is 0.94 and 0.97 respectively which suggest uniform distribution of error among both class.





Pig at different Position and the prediction of the model



- For independent testing, input from all 22 section were taken and prediction was made over them
- Predicted position of the pig is very close to actual position of pig in most cases

Conclusion

- The Multi-Input CNN model that was proposed which utilize both MFCC and STFT features can be used to classify percussion data and identify the location of the pig.
- The Multi-Input CNN with individual CNN network for each feature set and connected to a single dense layer for output was able to predict the presence or absence of pig with 95% accuracy during internal testing.
- The location of the pig could be estimated during independent testing.
- Future work could involve training on large data collected from multiple individuals to account for variations in percussion. Transformer architectures can be explored for further classification improvements.

Acknowledgements

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