Project Title: Percussion Based Pipe Inspection Gauge localization via Extreme Learning Machine and Neural Network based Machine Learning

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Introduction

- Pipe Inspection Gauges (PIGs) are widely used in the oil and gas and pipeline industry
- PIG misplacement frequently occurs, as debris can cause a PIG to get stuck along the pipe
- Machine Learning can localize PIG, however training deep learning techniques take large amounts of energy and time such as with Feed Forward Neural Networks (FFNNs)
- This project explores **Extreme Learning Machine (ELM) as a new ML method** balancing the accuracy of a Neural Network with cost-effectiveness of a shallow learning technique

Literature Review

- ELM is gaining notoriety as it blends shallow and deep machine learning, created in 2006 (Huang et al)
- ELM consists of a single layer feed forward neural network, no gradient descent needed
- What makes ELM unique from Neural Networks is it does not have a backpropagation training phase to determine gradient. Randomly assigns weights and biases to hidden layer
- Uses Moore-Penrose matrix inverse to determine the weight output from the hidden layer

Experimental Setup and Collection of Data / Additional Results

- Data was collected at frequency sampling rate of 48000 Hz
- 19 intervallic struck positions (separated by three inches each) on a 57 inch long stainless-steel pipe Training set consisted of 20 PIG present strikes at one interval, 5 PIG absent strikes at every other interval (PIG remained in same location)
- Testing set consisted of 5 strikes at each interval, repeated when the PIG was moved to each location

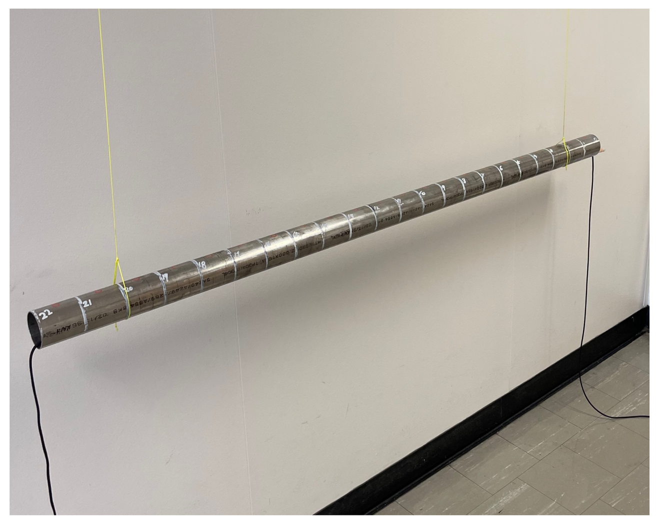


Figure 1 – Image of the stainless-steel pipe used for testing. PIG has string on both sides to move between intervals

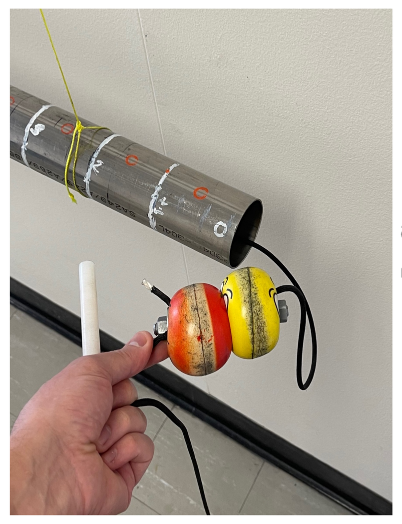


Figure 2 – Seen above is the PIG used for trials, inserted fully into stainless-steel pipe

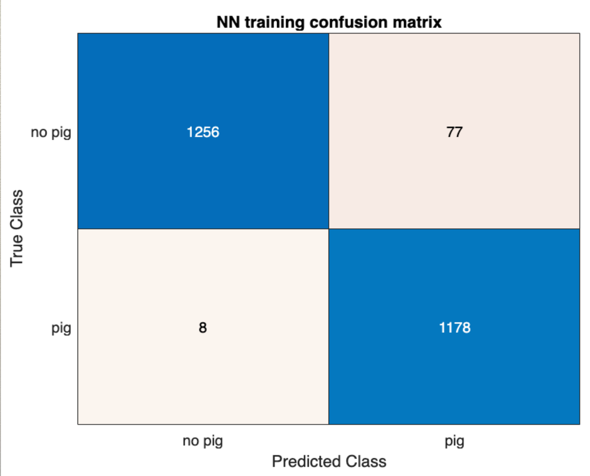
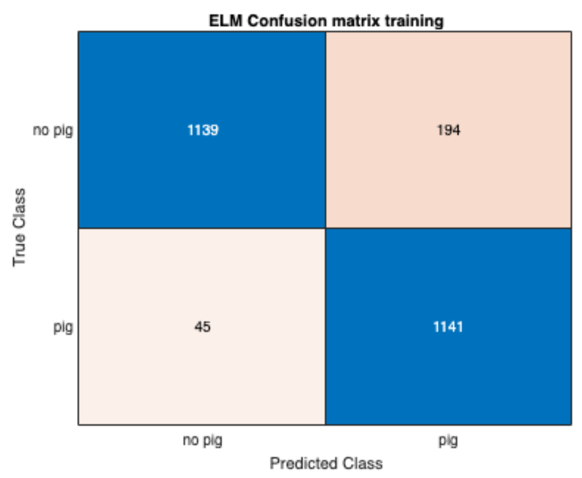


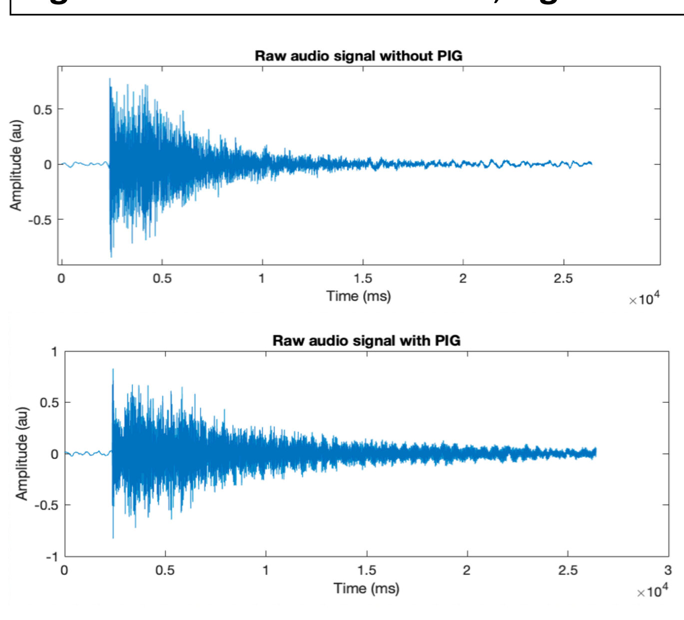
Figure 3 (above) – Confusion matrix of Feed Forward Neural Network training and validation

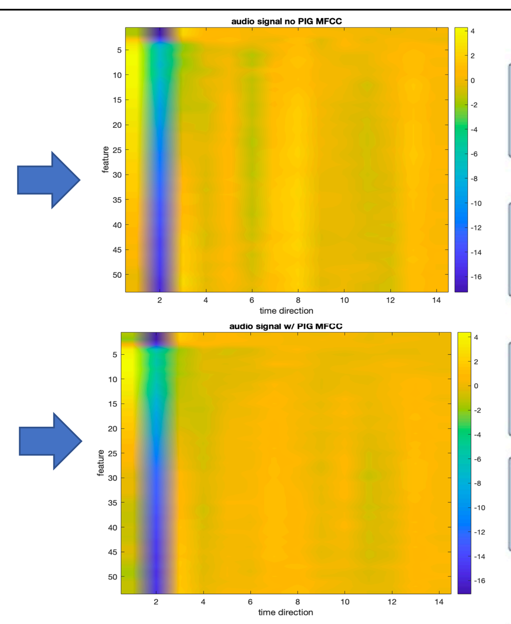
Figure 4 (below) – Confusion matrix of Extreme Learning Machine training and validation

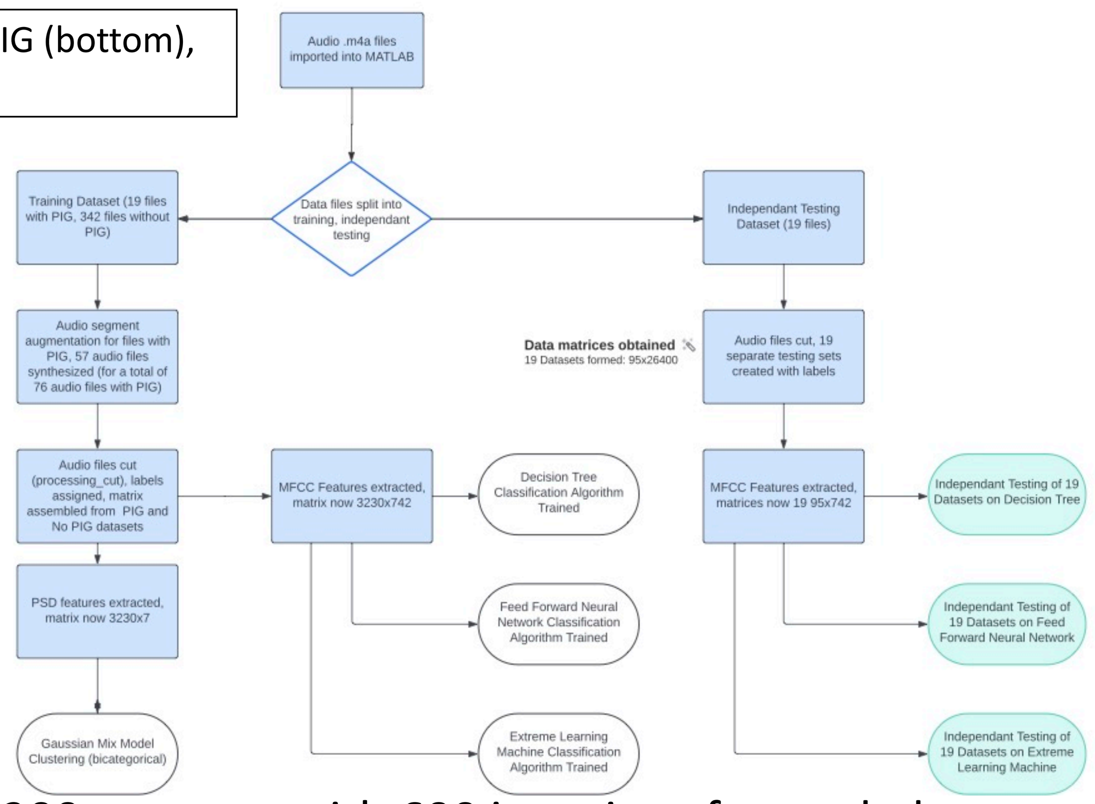


Method

Figures from left to right: **Fig. 5** - Raw audio signals of no PIG (top) and PIG (bottom), **Fig. 6** - MFCC transformations, **Fig. 7** flowchart showing data processing







- FFNN consisted of two hidden layers and a total of 200 neurons, with 600 iterations for grad. descent
- ELM consisted of one hidden layer with a total of 200 neurons, hidden layer weights randomized

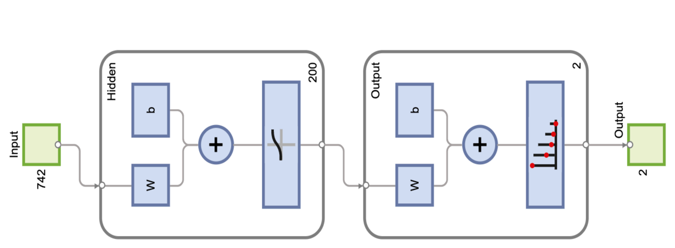
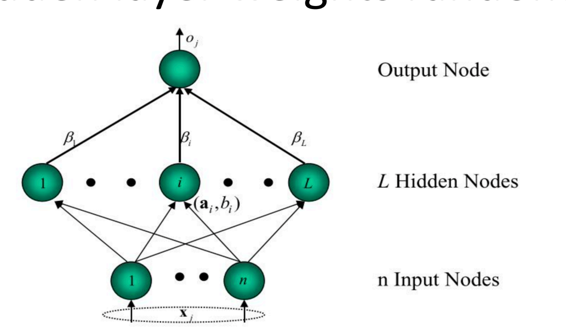
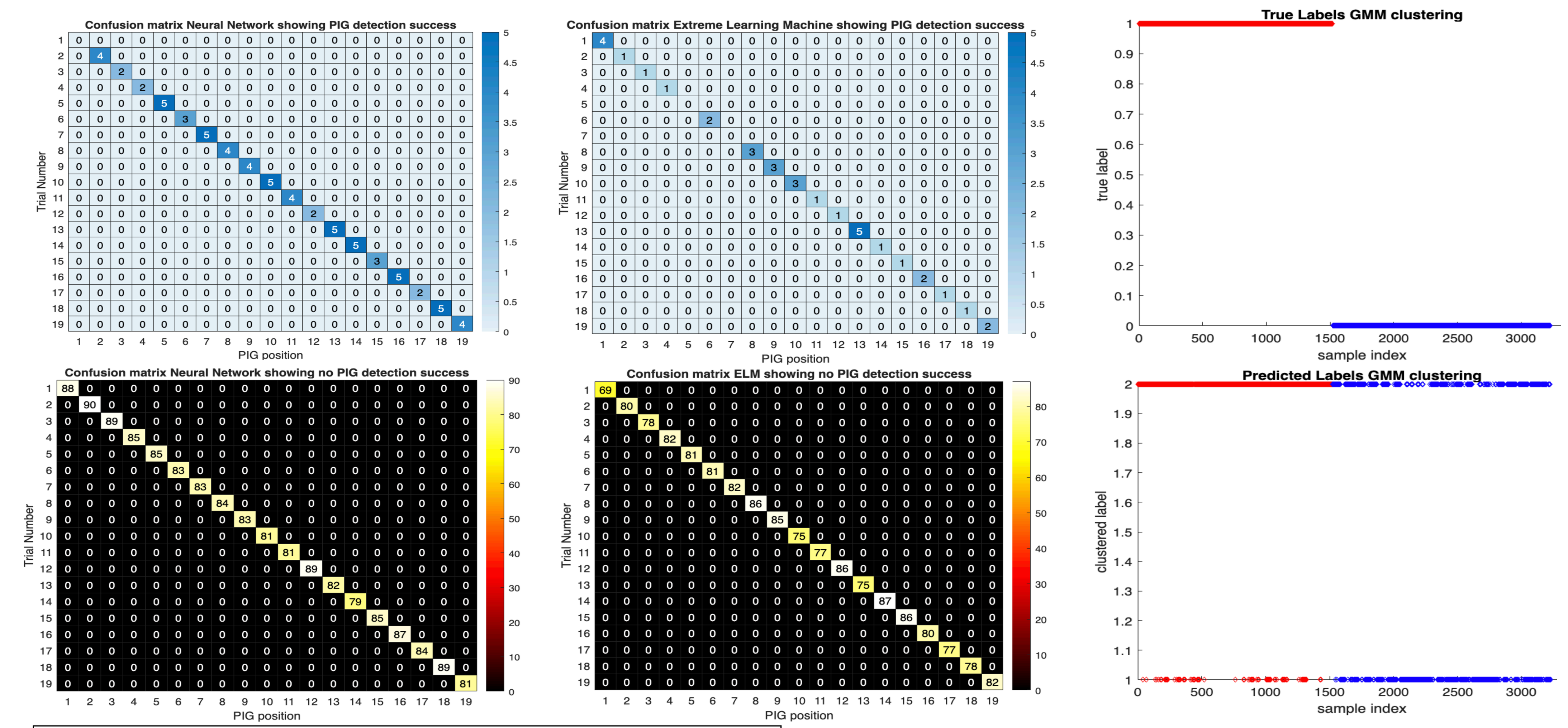


Figure 6 (left) – Diagram of FFNN used in model (logsig/softmax)
Figure 7 (right) – Diagram of ELM used (single layer FFNN)



Results, Analysis and Discussion, and Confusion Matrices (CM)



Figures from left to right: **Fig. 8** – CM for FFNN PIG and no PIG, **Fig. 9** - CM for ELM PIG and no PIG, **Fig. 10** GMM clustering results

Table 1 - Independent Test Results with ML methods

	Accuracy	$Precision_{PIG}$	$Precision_{NO\ PIG}$	$Recall_{PIG}$	$Recall_{NO\ PIG}$
Feed Forward Neural Network	92.58%	40.35%	98.41%	72.63%	94.04%
Extreme Learning Machine	89.75%	15.28%	84.72%	34.74%	89.30%
Decision Tree	88.03%	21.50%	77.42%	48.42%	90.18%
GMM clustering	74.06%	63.84%	87.50%	91.32%	54.04%

- Training validation results for both FFNN and ELM were extremely high, at 97% and 93% accuracies respectively
- Independent testing of FFNN and ELM models high accuracy, as seen in confusion matrices
- FFNN showed the highest efficacy, from accuracy/precision/recall standpoints in test data classification, compared to ELM and GMM
- Decision Tree ML method done as control, as it was able to separate into as many trees as necessary, its fair test results show that some data signals between 'no PIG' and 'PIG' share many common features
- Limitations of the experiment exist – test data was collected on separate day, microphone exposure to percussion could have varied (microphone covered in dust), as well as ambient noise conditions (restrooms, talking in hallway)
- ELM performed 60x faster in training dataset compared to FFNN – however it seems ELM struggles to differentiate percussion signals from the dataset as the PIG present precision data is low at 15%, compared to 40% for FFNN's.
- GMM method classified PIG present data very well, however struggled in classifying PIG absent data (recall results)
- As GMM classified PIG presence well, and ELM classified no PIG well, using both methods for future work could result in a very robust model that can execute training quickly (GMM and ELM train much faster than deep learning)

Conclusion

- **ELM is a new method seen the SMSL lab,** and performed classification better than well respected shallow learning techniques and clustering methods such as Gaussian Mixed Model and Decision Tree
- While in this study, FFNN with two hidden layers performs better than ELM, more distinguishable features in future work could see ELM have equal performance to FFNN, as seen with the training validation accuracies -- all while shaving valuable time and computing power/energy off of training
- Future studies intend to use piezoceramics, both on the pipe as well as within the PIG itself, to see if full automation of PIG detection can be done, as currently the need percussion strike in this method can be time consuming as well as unrealistic in underground or subsea environments

Acknowledgements

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