Project Title: Multi-Bolt Looseness Classification on a Plate Structure Using Percussion and Supervised Learning Algorithms

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Problem Statement

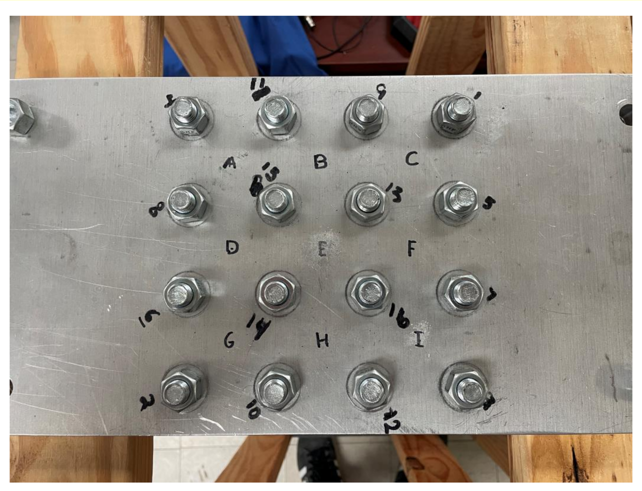
Bolted connections are exceptionally common, and they loosen over time. Failure to properly monitor these connections can lead to structure failure and death[1-6]. The goal of this research is to examine the ability of supervised machine learning algorithms to classify multi-bolt looseness scenarios on a set of aluminum plates. Seven different algorithms and four different signal processing feature sets will be used in testing in two cases, making for a total of 56 different percent accuracy results in testing. This will be comprehensive look into the validity of percussion for multi-bolt monitoring.

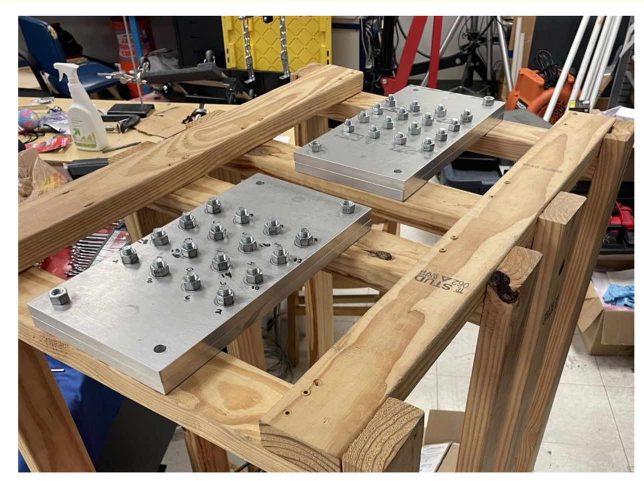
Brief Literature Review

- Bolt looseness on plates has been researched with other monitoring methods, but there's not much with percussion[1]
- Multi-bolt looseness monitoring with percussion has been with simple, unrealistic loosening scenarios[4,5,6]
- Other monitoring on plates has also primarily concerned single-bolt looseness[2,3]
- Finally, to my knowledge, there is not research that explicitly explores combining different feature sets into single matrices

Experimental Setup and Collection of Data

- All the bolts were numbered, and the center of each 4-bolt square was lettered to track tapping location
- All bolts were present and were tight (40 ft-lb) unless otherwise specified
- A set of two aluminum plates on a wooden cart was used to test two multi-bolt looseness cases: testing for number of bolts loose (Case 1) and presence of loose bolts (Case 2)





- 30 taps were used for training and testing while 10 were used in validation for both cases
- **Case 1**
  - To test for detecting number of loose bolts, there were three classes of data in Case 1: 2, 4, and 10 loose bolts
  - The tapping location in Case 1 did not change and was always in the middle of the plate
- **Case 2**
  - To test for detecting presence of loose bolts, there were two classes of data in Case 2: 0 and 2loose bolts
  - The tapping location of Case 2 was tested at points A, E, and I
- Tables 1 and 2 show in-depth properties for each audio file taken for this project, including which bolts were loose, tapping location, and number of taps for training, testing, and validation

Table 1: Case 1 Loose Bolt Scenarios

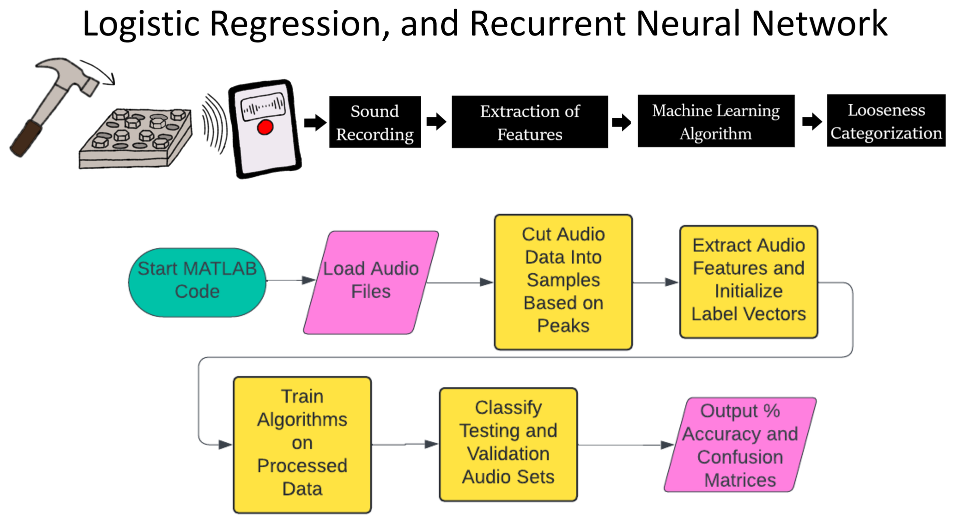
Subcase #	Loose Bolts	Tapping Location	Training Taps	Testing Taps	Validation Taps
1	1,2	Point E	30	30	10
2	13,14	Point E	30	30	10
3	15,16	Point E	30	30	10
4	3,4	Point E	30	30	10
5	5,6,7,8	Point E	30	30	10
6	5,7,8,9	Point E	30	30	10
7	9,10,11,12	Point E	30	30	10
8	All Outer Bolts	Point E	30	30	10

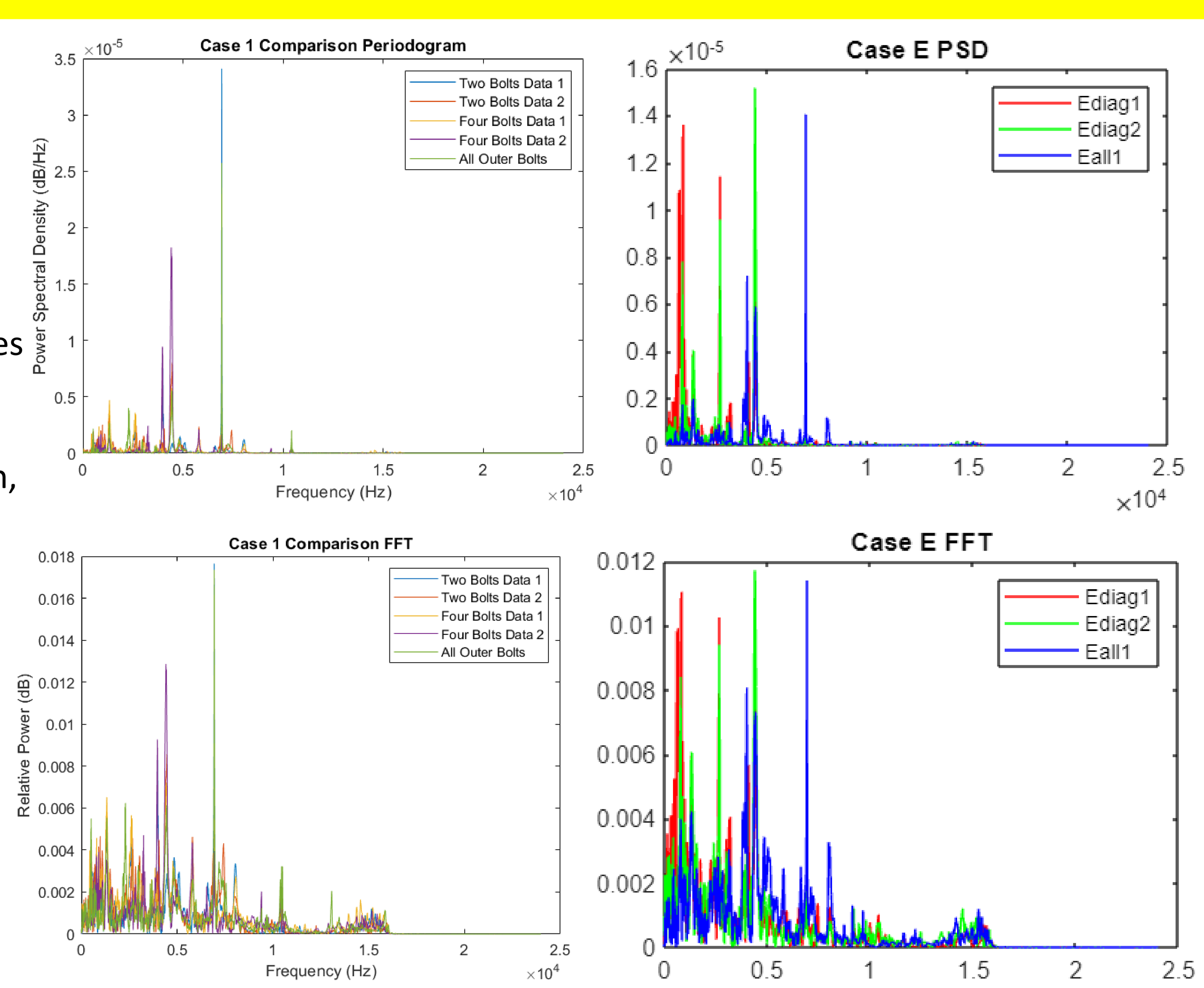
Table 2: Case 2 Loose Bolt Scenarios

Subcase #	Loose Bolts	Tapping Location	Training Taps	Testing Taps	Validation Taps
1	4, 15	Point A	30	30	10
2	8, 11	Point A	30	30	10
3	None	Point A	30	30	10
4	13, 14	Point E	30	30	10
5	15, 16	Point E	30	30	10
6	None	Point E	30	30	10
7	12, 7	Point I	30	30	10
8	16, 3	Point I	30	30	10
9	None	Point I	30	30	10

Methods

- Multiple feature matrices created: Power Spectral Density (PSD), Fast Fourier Transform (FFT), Mel-Frequency Cepstral Coefficients (MFCC) and combined PSD + FFT
- This is one of the first instances of combining audio feature sets to create a larger set for training and testing, using concatenation of the PSD and FFT matrices
- Seven algorithms used to classify data: K-Nearest Neighbors (KNN), Decision Tree (DT), Neural Network (NN), Support Vector Machine (SVM), Linear Regression, Logistic Regression, and Recurrent Neural Network





Results, Analysis and Discussion

- Between all four methods of feature extraction, FFT and the combined PSD + FFT feature sets generally performed the best and most consistently between testing and validation

Summary of Performance:

- **Case 1**
  - KNN and NN algorithms performed the best
  - FFT features performed the best in both testing and validation
  - The MFCC features performed second best
  - The major point of weakness was the intermediate "4 Loose Bolts" class
  - Classifying the "10 Loose Bolts" class was almost always done perfectly
- **Case 2**
  - RNN and Logistic Regression performed the best
  - PSD + FFT features performed the best in testing and validation
  - FFT performed second best
  - The major point of weakness was classifying "2 Loose Bolts" data as "0 Bolts Loose"
  - The combined feature set could perform up to 10% better than PSD or FFT individually in some cases
- Overall, work needs to be done to improve intermediate class identification for case 1 and improving classification of false negatives in class 2
- Further exploration of combining audio feature sets could make some features more flexible and help retain accuracy

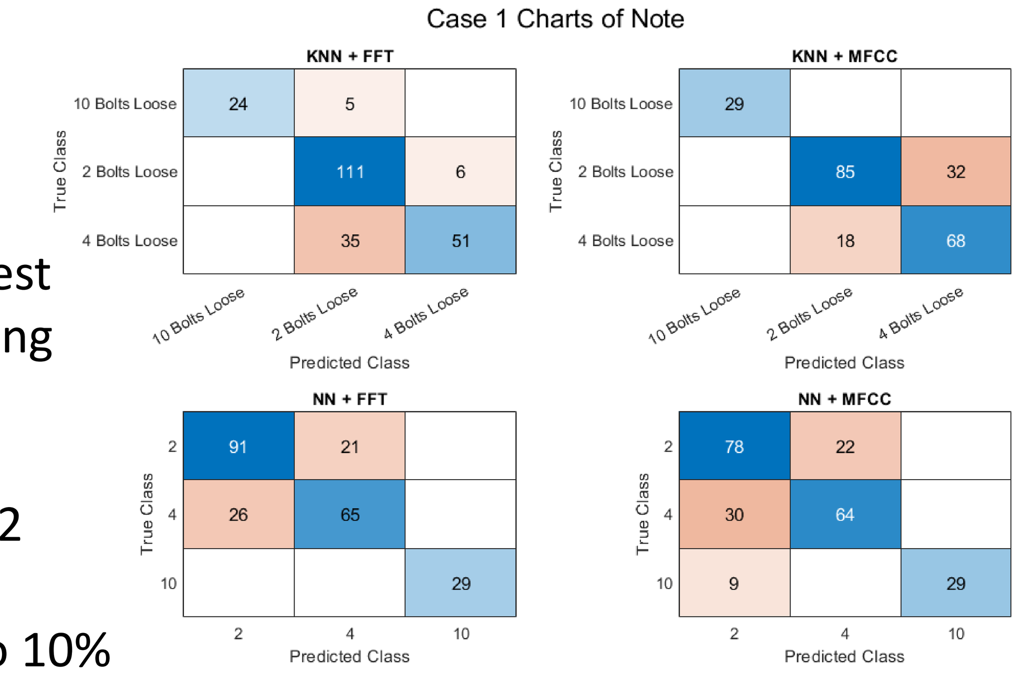
Case 1 Algorithms And Feature Accuracies of Note

	Testing FFT	Validation FFT	Testing MFCC	Validation MFCC
KNN	80.17	75	80.17	75
NN	79.72	69.6	74.14	80.55

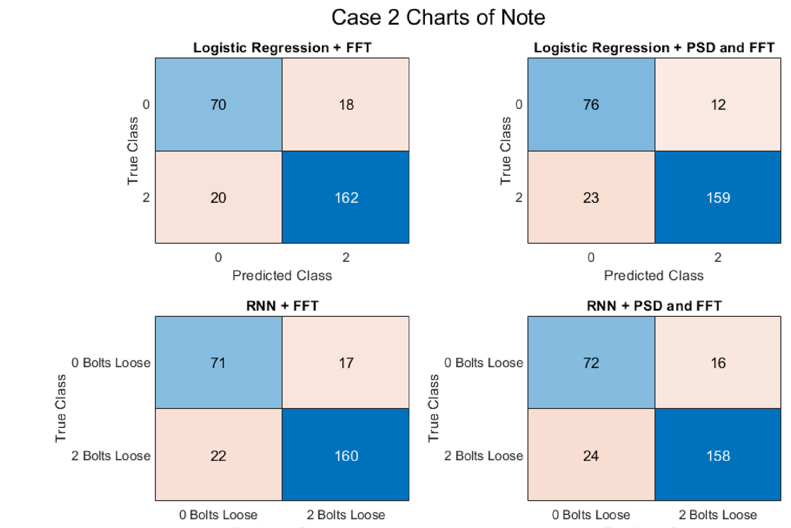
Case 2 Algorithms And Feature Accuracies of Note

	Testing PSD + FFT	Validation PSD + FFT	Testing FFT	Validation FFT
RNN	84.81	69.41	84.44	69.41
Logistic Regression	87.04	75.29	85.93	75.29

Case 1 Charts of Note



Case 2 Charts of Note



Conclusion

- Overall, the results gained in this study are promising for multi-bolt looseness monitoring, with classification of number of loose bolts generally ranging about 70-80% accurate and classification of loose bolt presence being about 80-90% accurate
- Furthermore, the use of combined feature sets is especially promising for identifying the presence of loose bolts
- Future research could introduce intermediate classes into Case 2 to identify how loose the present loose bolts are
- Given the short scope of the project, supplying this data to graduate students for further examination could also improve results

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