Machine Learning Approaches for Acoustic Evaluation of Metal Plates

Pratik Poudel, Graduate Student

Department of Mechanical Engineering, Cullen College of Engineering

Problem Statement

- Presence of metal cavities decreases structural integrity in critical industries like aerospace and automobile, leading to catastrophic failures.
- Machine learning techniques analyze acoustic signals to detect cavities reliably and cost-effectively, thus avoiding failures and extending material lifespan.
- Key challenges involve managing noisy and variable signal data, and developing models that achieve the right fit without overfitting

Brief Literature Review

- Park et al. (2022) investigated using machine learning for cavity detection in metallic materials training machine learning algorithms on acoustic emission data, the sounds emitted by materials under stress and identify patterns in the acoustic data that corresponded to the presence of cavities within the metal.
- Yan et al. (2019) explored the use of Convolutional Neural Networks (CNNs) on labeled acoustic recordings (with and without cavities) and achieved promising results in classifying defects like cavities based on the complex relationships learned within the acoustic data.
- Some patents related are:
  - US Patent 10,821,902 (2020): "Method and Apparatus for Acoustic Emission Testing Using Machine Learning" by Baker et al. This patent describes a system that utilizes machine learning algorithms to analyze acoustic emission data from materials under stress. The identified patterns can be indicative of cracks or other defects.
  - WO 2021132242 A1 (2021): "Method and Device for Non-Destructive Testing of Metallic Materials" by Kim et al. (PCT/KR2021/004022). This international patent application describes a method for NDT of metallic materials using acoustic emission and artificial intelligence (AI). The AI analyzes the acoustic data to identify and classify defects.
  - US Patent 11,230,224 (2022): "Acoustic Emission Sensor for Non-Destructive Testing" by Park et al. This patent details a novel acoustic emission sensor design that offers improved sensitivity and directionality for detecting defects in composite materials.

Experimental Setup and Collection of Data

- Cavities were made on the metal block and covered by a metal plate to conceal them
- Grids were made on the other side of the plate
- A metal was used to record the sound by using percussion on each of the grids

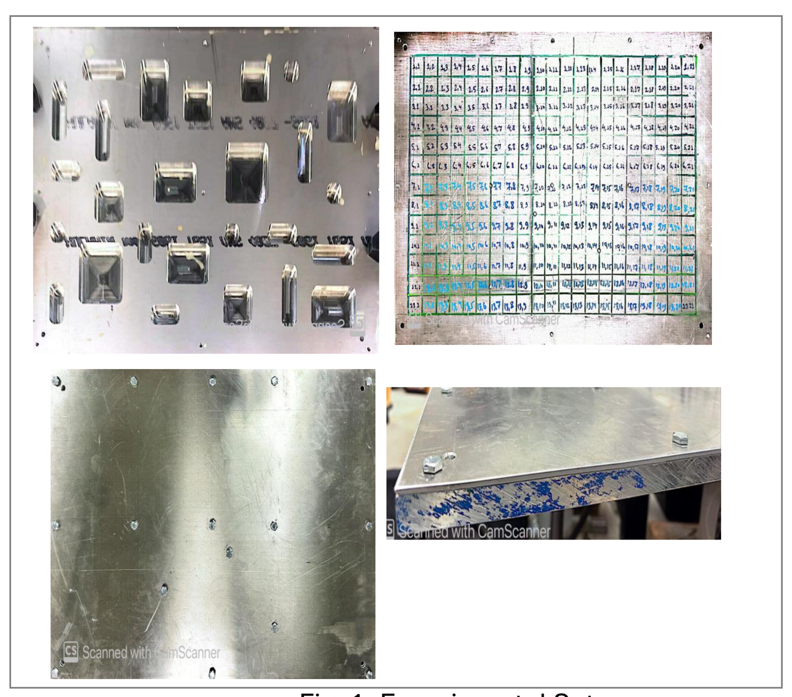

Fig. 1. Experimental Set up

Fig. 2. Recording data

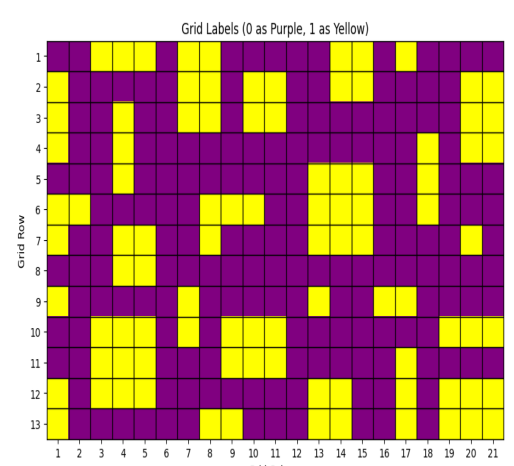

Fig. 3. True labels of grids (yellow: presence of cavity, purple: no cavity

Total number of Grids: 273 (13*21)
Number of single-hit signals: 2730
Number of single-hit signals after preprocessing: 2630
Number of datasets with label 0 (without cavity): 1714
Number of datasets with label 1 (with cavity): 916
For independent verification:
Test set Grids: 10, 10 to 13, 21 (48 grids, 476 datasets)
Training set Grids: Rest of the grids (225 grids, 2154 datasets)

Method(s)

- MFCC was used as feature to extract the characteristics of signals
- Different shallow methods were applied for classifications which includes decision tree, support vector machine, and logistic regression
- Deep learning methods such as deep neural networks, Long short-term memory recurrent neural network (LSTM-RNN), and Convolutional Neural Networks (CNN) were used as machine learning methods
- Three different types of test were done based on the selection of test set:
  - Train-test split in ratio 80:20 (dependent)
  - One dataset from each grid as test set (dependent)
  - Dataset from grids 10,10 to 13,21 as test set (independent)
- For independent test of Convolutional Neural Network (CNN) , mfcc features were extracted and the test set was taken from the grids 10,10 to 13, 21. Then, training set was fed to train a neural architecture for classification.
- Using CNN for sound recording for detection of the cavities is a less explored field as RNN is normally used for time series

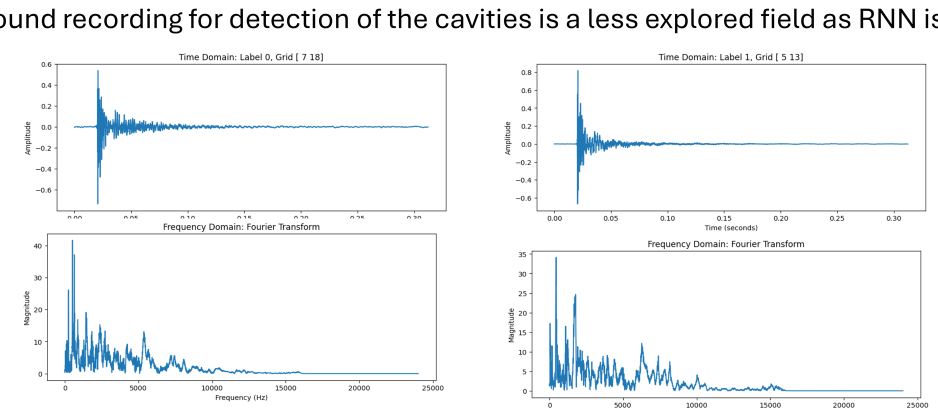

Fig. 5. Comparison of labels on time and frequency domain

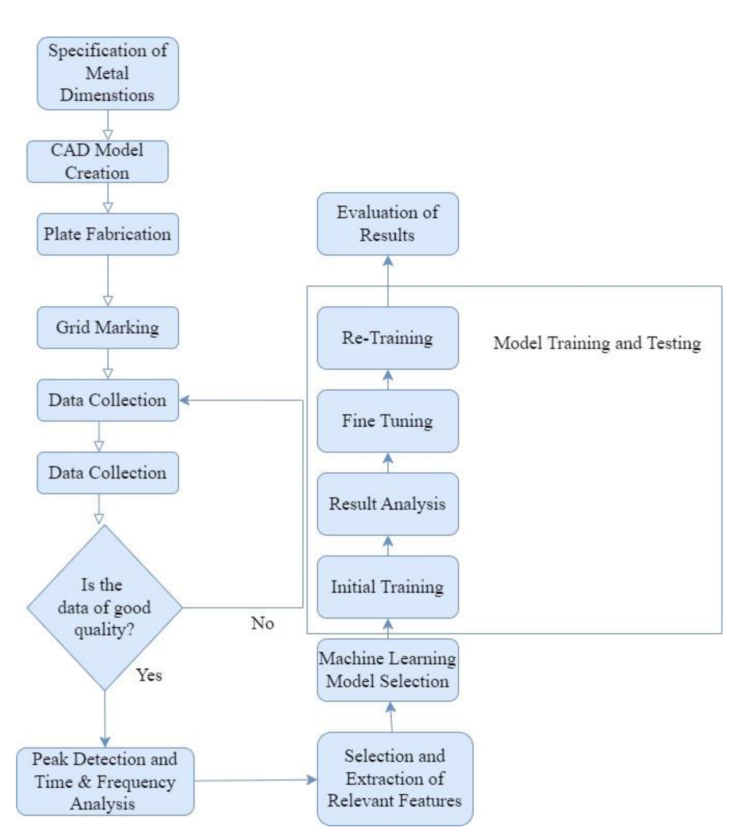

Fig. 6. Flowchart of the project

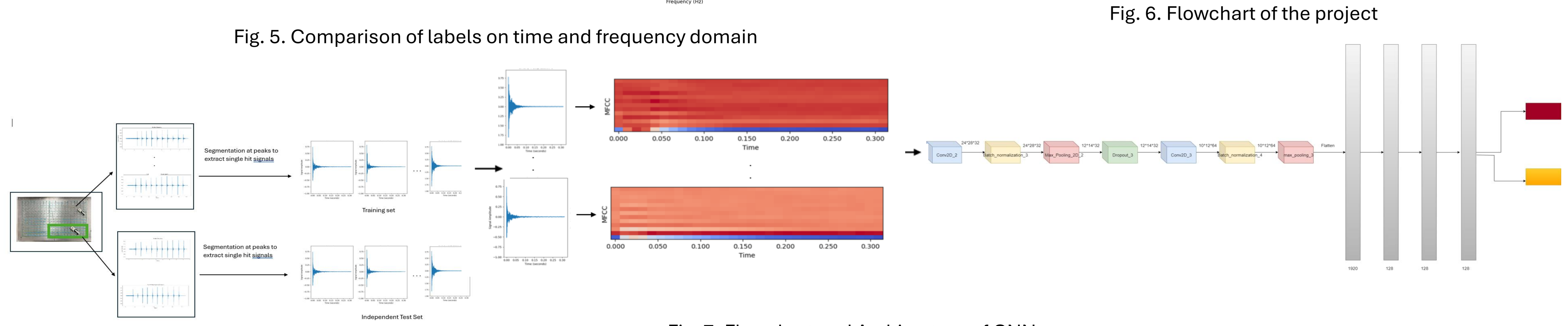

Fig. 7. Flowchart and Architecture of CNN

Results, Analysis and Discussion

Machine Learning Methods / Types of test set		Train: test split 80:20 (Dependent test)	One dataset from every grid as test set (Dependent test)	Dataset from 10,10 to 13,21 as test set (Independent test)
Shallow Learning Methods	Decision tree	72.81%	73.26%	58.33%
	Support Vector Machine	80.23%	73.99%	66.67%
	Logistic Regression	90.3%	83.88%	70.83%
Deep Learning Methods	Deep neural networks	88.02%	74.35%	66.67%
	Recurrent Neural Networks	83.84%	74.73%	70.83%
	Convolutional Neural Networks	84.03%	80.59%	72.06%

Fig. 8. Accuracy for different shallow and deep learning methods

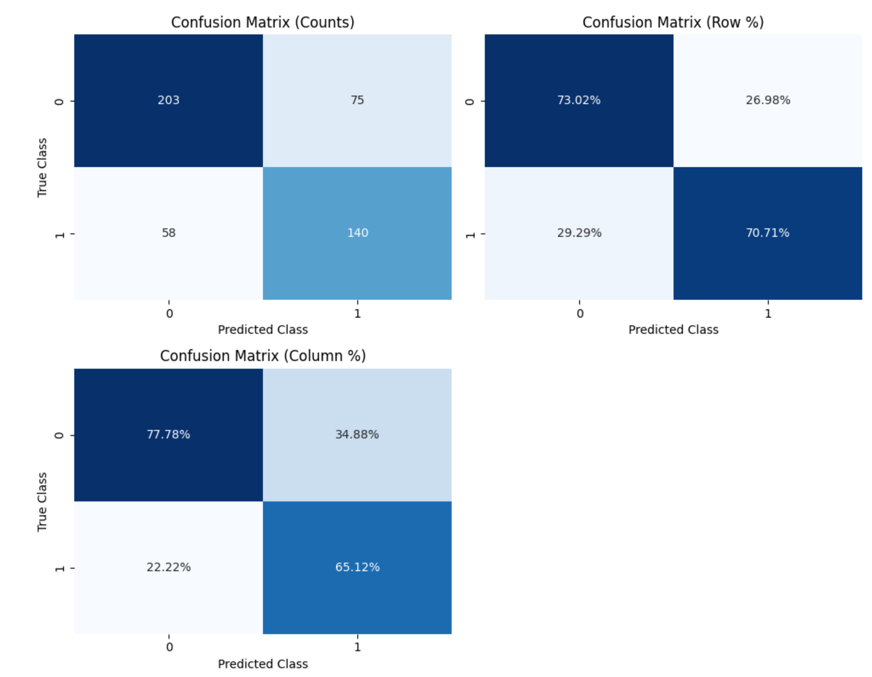

Fig. 9. Confusion Matrix for Independent Test for CNN

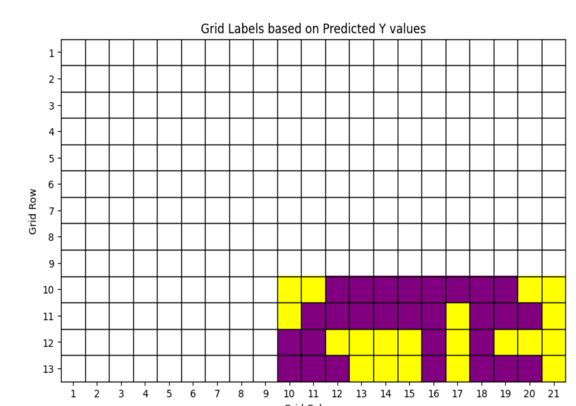

Fig. 10. Plots of predicted label Independent Test on CNN (yellow for grids with label 1 and purple for label 0

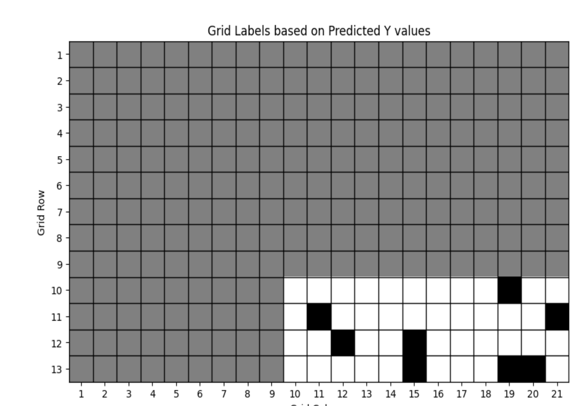

Fig. 11. Plots of comparison of predicted and true value for Independent Test on CNN (white for True, black for False)

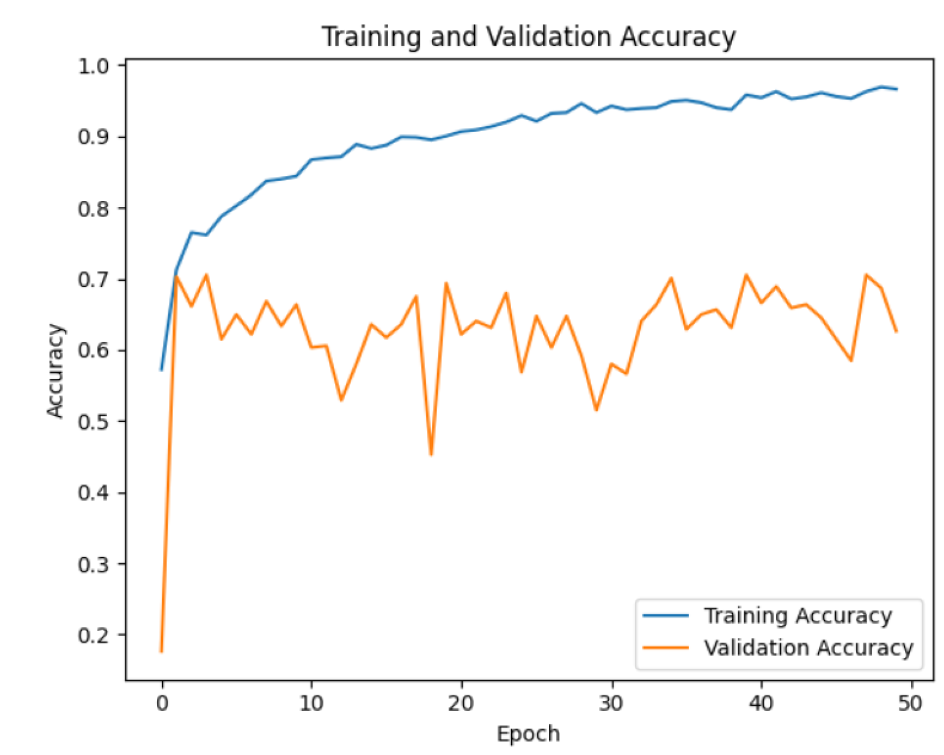

Fig. 12. Training and Validation Accuracy for CNN model

- Mainly three different plots are used to analyze the results, viz. confusion matrix, plot of labels, comparison of predicted and actual labels
- Among shallow learning methods, logistic regression is found to produce better results.
- Among deep learning methods, convolutional neural network is found to produce better results
- The signals of different labels weren't readily distinct and demand fine tuning.
- The number of datasets are little less for running deep learning models
- The comparison plot shows that the grids at edges are difficult to detect, which may be due to more echo of sound at the edges
- Project shows promising preliminary results to detect the cavities and the model can be improved with more data

Conclusion

- Percussion-based signals can be used for classification problems for detection of cavities in metals
- With right features and enough datasets, high accuracy can be achieved for cavity detection
- Deployment of detection can be a good learning process for future projects
- More feature extractions and data collection can further increase the accuracy

Acknowledgements

The financial support from Midstream Integrity Services (MIS) and technical support from Smart Materials & Structures Lab (SMSL) and Artificial Intelligence Lab for Monitoring & Inspection (AILMI) at UH.

References

- Sun, Y., et al. "Lamb wave-based cavity detection in metallic plates using a time reversal method." Sensors and Actuators A: Physical 302 (2020): 111722.
- Park, J.-M., et al. "Non-destructive evaluation of cavities in metallic materials using machine learning with acoustic emission data." Materials Science and Engineering: A 830 (2022): 142223.
- Li, C., et al. "Improved cavity detection in metallic plates using support vector machine with grey wolf optimizer." Measurement Science and Technology 30.8 (2019): 085002.
- Yan, Y., et al. "A convolutional neural network approach for steel bar defect recognition based on acoustic emission signals." Sensors 19.11 (2019): 2587.
- Yu, P., et al. "Multi-sensor information fusion for nondestructive testing of cavities in metallic plates based on the improved grey relational analysis method." Sensors 18.1 (2018): 190.
- Zhu, J., et al. "Physics-informed machine learning for damage prognosis of composite laminates based on acoustic emission data." Composite Structures 236 (2022): 111884.
- Yan, G., et al. "A review of recent advances in acoustic emission-based structural health monitoring." Sensors 19.12 (2019): 2844.
- Sun, Z., et al. "In-situ monitoring of laser powder bed fusion using acoustic emission and machine learning." Additive Manufacturing 32 (2020): 101051.