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Improving Detection Accuracy of Microseismic Activity During Geologic Carbon Storage Using a Machine Learning Method

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Motivation & Summary

Machine learning/deep learning (ML/DL) models have emerged to improve the detection of seismic events more accurately and efficiently [1-3]. However, microseismic events, such as those induced by CO_2 injection into the subsurface, remain challenging due to their low event signal energy and a limited number of events.

In this study we implement ML approaches for event detection of induced microseismic activity at the Illinois Basin Decatur Project (IBDP) [4] where a million metric tonnes of CO2 has been injected (2011-2014) and a number of microseismic clusters are identified [5, Figure 1].

Objectives

- Develop convolutional neural network (CNN) models to improve event detection
- Evaluate the impact of additional physical properties in ML model on event detection accuracy
- Evaluate the data preprocessing strategy to improve event detection using CNN models

Data Processing

We focus on microseismic waveform data over a short time period (Feb. 27 to Mar. 12) when a total of 612 events are located in the catalog. We use three channel time-series data from the lowest geophone. Waveform conversion to spectrogram per channel includes Detrend (mean) -> Bandpass (10-400 Hz) -> STFT (window=128) -> Normalized by log scaling -> Rescale (0 to 1).

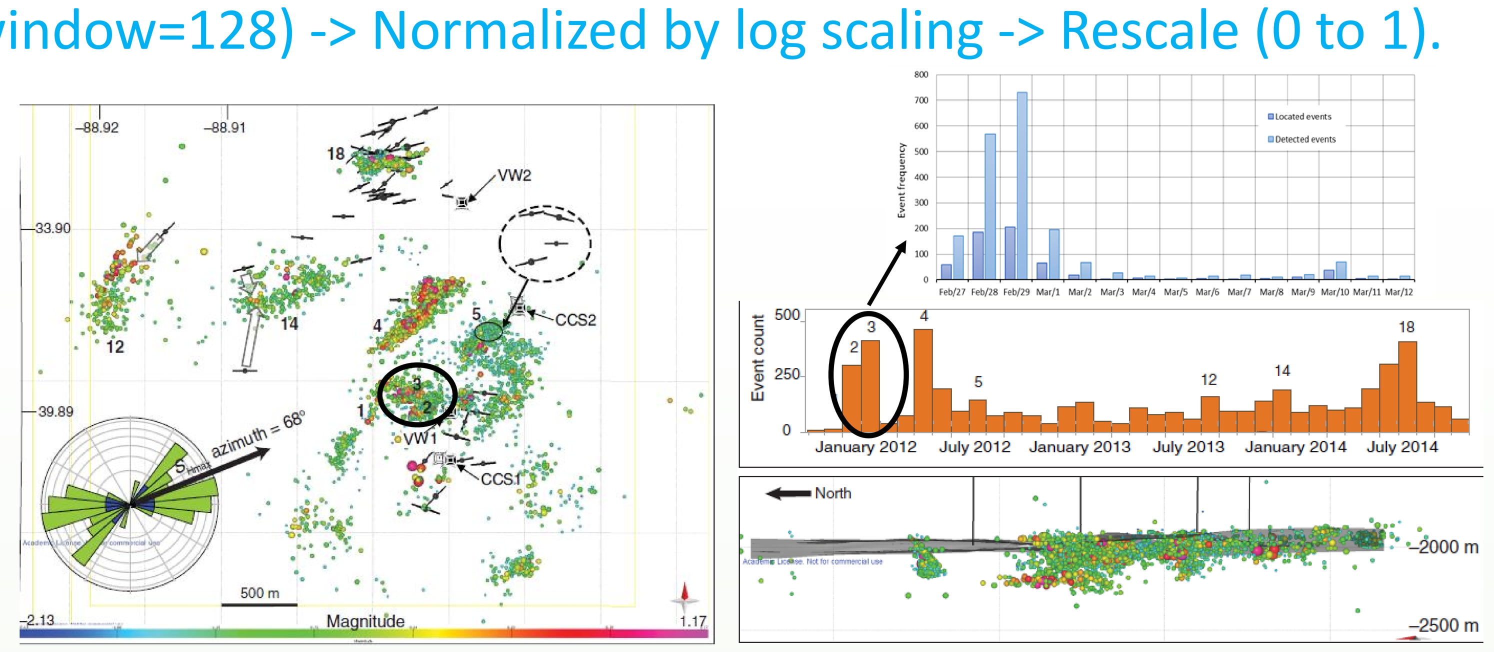

Figure 1. IBDP microseismic event clusters and a number of events over time with the vertical overview of clusters [copied from [5]]

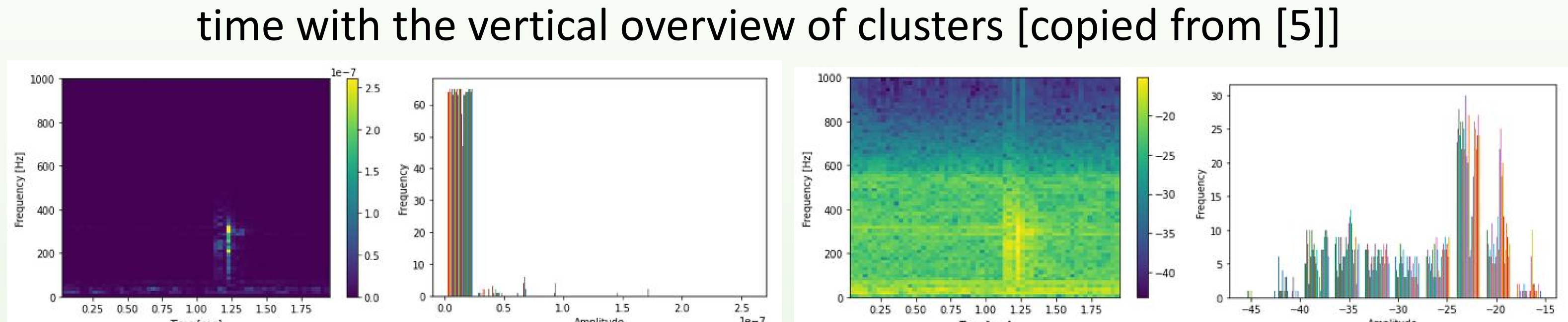

Figure 2. Spectrogram and amplitude histogram (left) before log scaling and (right) after log scaling

Wave Physical Properties

Feature extraction using random forest model was conducted to identify Mel-Frequency Cepstrum Coefficients (MFCC) to represent energy of the microseismic event.

Methodology

Due to the limited number of waveform samples, the models consist of simple CNN architectures with a relatively low number of trainable parameters (~200K) to avoid overfitting. Multilayer perception (MLP) block is used to take MFCC data as input. Features from both CNN and MLP blocks are concatenated before a final dense layer, leading to the final prediction (event, no event) output.

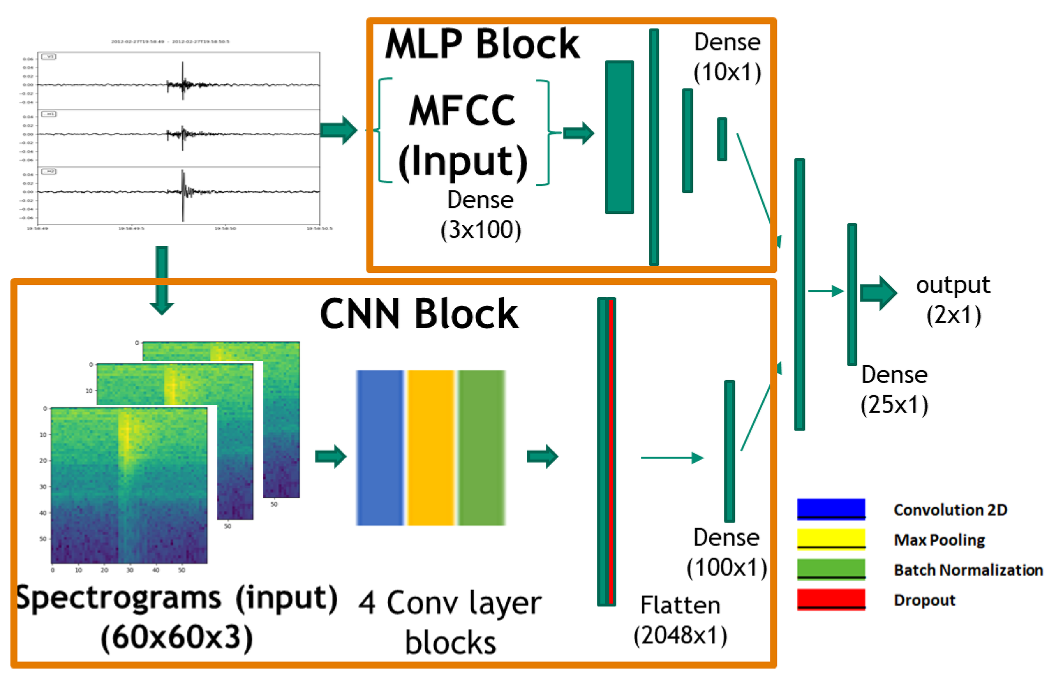

Figure 3. Schematic of DL model architectures and their corresponding input data format.

Key training results:

- Models with proper input normalization optimize better.
- CNN best loss = ~1×10^{-6}
- CNN+MLP best loss = ~ 1×10^{-7}

Table 1. Comparison of events on catalog versus predicted with trained ML models.

	Mar/1
Detected	196
Located	66
CNN	532
CNN+MLP	987

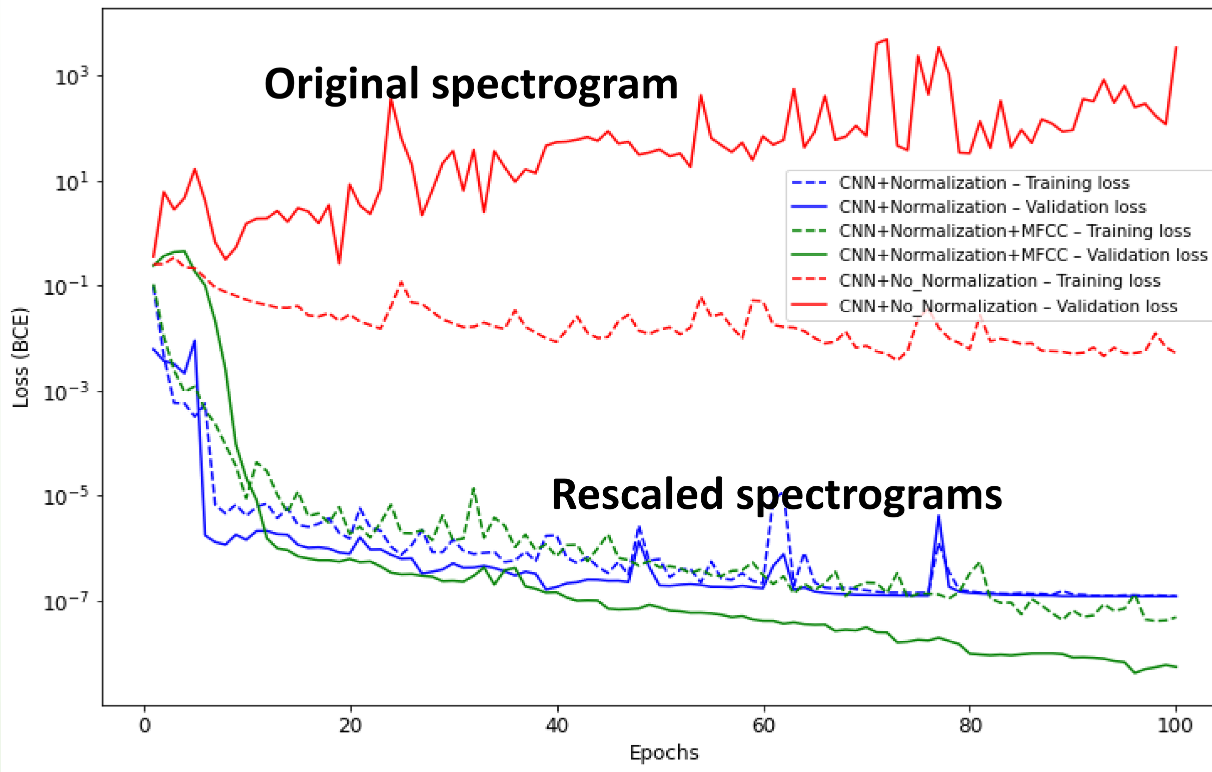

Figure 4. Binary cross-entropy loss values over epochs for each DL model. Dashed and solid curves represent training and validation losses, respectively.

Results

- Both DL models detect close to as many or more events than those reported in the IBDP catalog (Figure 5)
- Models predict events registered in the catalog (A-B) and newly detected events (C-D) (Figure 6).

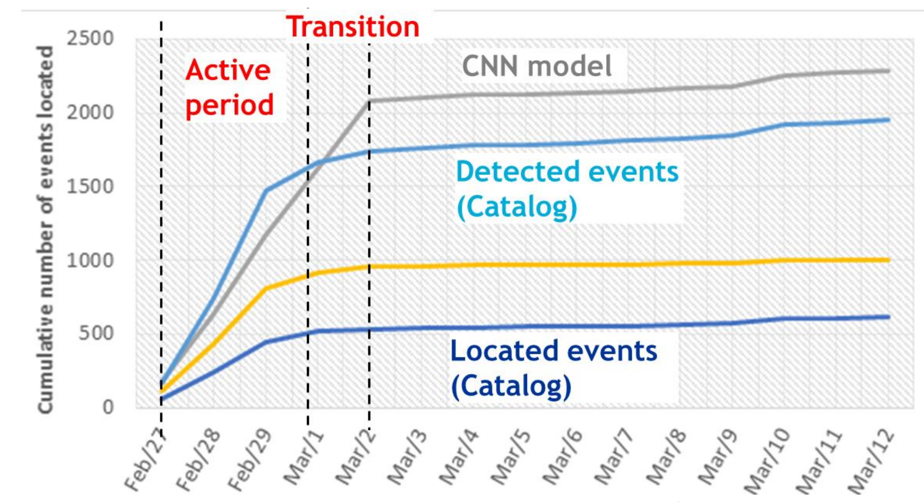

Figure 5. Cumulative number of detected events through the CNN and cataloged events.

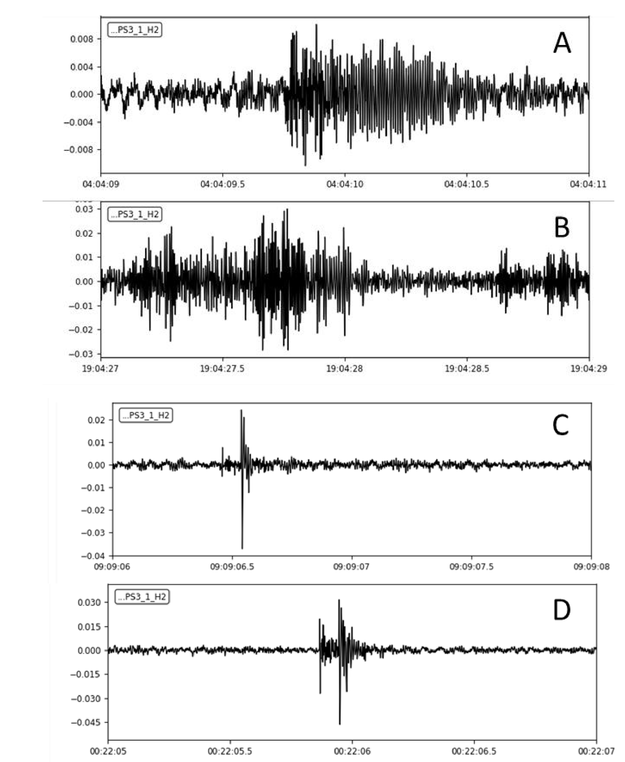

Figure 6. Microseismic detection by DL models on continuous raw waveform data

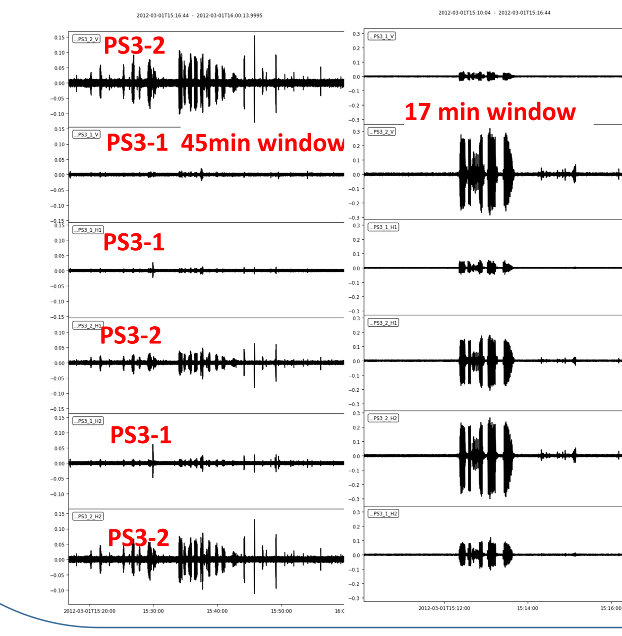

Figure 7. Long period and long duration events detected by trained ML model (March 1, 2012)

Summary & Future work

- The usage of spectrogram and data normalization as a pre-processing improves detection accuracy of CNN models significantly even with 612 event data per cluster.
- Additional physical data in CNN + MLP model seems to improve detection accuracy slightly better
- Application of trained model for continuous raw microseismic waveform data for Feb-Mar data leads to find long period and long duration (LPLD) type waveform data, suggesting the fault type is likely different from other faults
- Integration of event detection, phase picking, and source location is in progress

References

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