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Automatic Phase Picking of Microseismic Data based on PhaseNet: A Case Study of the TOC2ME Dataset

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Summary

In this study, we evaluated the performance of *PhaseNet*, a convolutional neural network (CNN)-based seismic picker, in detecting the first P and S arrivals in microseismic signals. To achieve this, we utilized the Tony Creek Dual Microseismic Experiment (*TOC2ME*) dataset, a well-studied open dataset for microseismic analysis, to assess PhaseNet's effectiveness in event detection and phase picking. Instead of resampling the data to 100 Hz—the sampling rate used in PhaseNet's training data (30-second windows with 3001 data points)—we retained the original 500 Hz sampling rate of the TOC2ME data. This adjustment allowed PhaseNet to process 6-second windows containing 3001 data points (500 Hz × 6 s), aligning more closely with its training conditions of one event per window. By reducing the number of events per window to 1-2, this approach enhanced the model's ability to detect small-magnitude microseismic signals.

Using this method, we applied PhaseNet to the TOC2ME data, subsequently associated the picked arrivals with the Rapid Earthquake Association and Location (REAL) package, located events using the Hypoinverse package, and refined the locations with the HypoDD package. The results showed that the pre-trained PhaseNet model can successfully detect 17,655 events, covering around 98% of the events in the Eaton et al. (2018) catalog and about 81% in the Igonin et al. (2020) catalog. These findings highlight PhaseNet's capability to reliably pick the first arrivals of microseismic signals, demonstrating its potential for improving microseismic monitoring.

Introduction

Over the past several decades, human activities such as mining, oil production, and geothermal energy extraction have markedly expanded underground operations (Moein et al., 2023). Most of these activities disturb the natural stress equilibrium beneath the Earth's surface, leading to small earthquakes known as induced seismicity. These events, often referred to as microseismic signals, are characterized by their low magnitudes and low signal-to-noise ratio (SNR) (Maxwell, 2014). While such induced earthquakes are generally imperceptible to humans, they can pose a risk by potentially triggering larger earthquakes on nearby faults, making their monitoring essential.

Detecting and picking the first arrivals of these signals is challenging due to their low SNR, which renders traditional automated methods like short-term amplitude (STA) and long-term amplitude (LTA) ratio techniques inefficient and inaccurate (Anikiev et al., 2023). Manual picking of P- and S-phase arrivals, on the other hand, is hard and time-consuming. In recent years, deep learning (DL) methods have shown great promise in event detection and phase picking of earthquake data (Anikiev et al., 2023; Mousavi & Beroza, 2022). However, these methods often cannot be directly applied to or generalized for microseismic data because the characteristics of their training data differ from those of microseismic datasets (Lim et al., 2024). In this research, we aim to optimize and evaluate the performance of

PhaseNet, a CNN-based deep learning picker originally trained on earthquake data, for microseismic data. Our approach focuses on enhancing the model's performance without retraining it.

Data

The microseismic dataset used in this study is the Tony Creek Dual Microseismic Experiment (TOC2ME) dataset. It was acquired during a research project led by the University of Calgary and conducted during hydraulic fracturing in the Kaybob-Duvernay horizon of the Fox Creek area, Alberta. The data collection spanned approximately 38 days in late 2016 (Eaton et al., 2018). The dataset includes 69 stations, each equipped with multiple geophones: three single-component geophones installed at depths of 12, 17, and 22 meters in a borehole and one three-component geophone installed at a depth of 27 meters (Eaton et al., 2018). Additionally, six broadband seismometers were installed at six stations, and one station was equipped with a ground-motion accelerometer (Eaton et al., 2018).

In this study, we used the three-component geophone data, recorded at a sampling rate of 500 Hz. The dataset includes four published catalogs, comprising the Eaton et al. (2018) catalog, which contains 4,083 events spanning the whole period (including the most significant events) (Eaton et al., 2018), and the Igonin et al. (2020) catalog, which identifies 18,040 events across the dataset (Igonin et al., 2021). These catalogs make the ToC2ME dataset a valuable resource for evaluating the performance of deep-learning pickers.

Method

PhaseNet is a modified version of U-Net architecture (Ronneberger et al., 2015) to handle 1-D time-series data (Zhu & Beroza, 2019). This machine learning model processes 30-second windows of three-component seismic data and outputs three probability functions: P-wave arrival, S-wave arrival, and noise. The first arrivals are identified by applying thresholds to these probability functions, with peaks above the threshold being selected as the first arrivals. The model was trained on over 700,000 100 Hz unfiltered waveform samples from northern California with P and S phases labelled by analysts (Zhu & Beroza, 2019). Each training window included P- and S-wave arrivals, but the arrival positions within the window may varied. Before input to the model, each component of the data was normalized by subtracting its mean and dividing by its standard deviation (Zhu & Beroza, 2019).

A significant difference between the PhaseNet training data and microseismic data lies in the presence of multiple events in 30-second microseismic windows. PhaseNet's training data typically contains only a single event per 30-second window. Consequently, the model may fail to detect additional events within a window. Furthermore, high-amplitude events can suppress smaller events in the same window during normalization, reducing the model's ability to identify them.

To apply PhaseNet, the dataset must be resampled to 100 Hz to match the 30-second, 3001-point windows used during the model's training. However, PhaseNet's performance relies on the number of data points rather than the overall waveform window duration. Therefore, we propose that rather than resampling to 100 Hz, directly use 3001 data points from 500 Hz (original sampling rate) microseismic data, corresponding to a 6-second window. This approach avoids the normalization drawbacks, aligns the data more closely with PhaseNet's training conditions, and significantly improves detection performance.

Figure 1 presents a 30-second, three-channel recording at 100 Hz input into PhaseNet, alongside its corresponding 6-second segments at 500 Hz after processing. Examining the 30-second window at 100 Hz sampling rate reveals two closely spaced seismic events: one at approximately 11 seconds and another around 13.5 seconds, with the first event exhibiting a lower amplitude compared to the second one. Our investigation shows that when the resampled 100-Hz 30-s data (Figure 1a, c, e) are fed directly into PhaseNet, the first event is reliably detected. This could be attributed to several factors, including its lower amplitude, the closeness of the two events, and the difficulty in detecting two events within a single window. In contrast, when the original 30-second 500-Hz window is divided into five segments of 6 seconds each (each still containing 3001 data points), these two events are separated into different windows (Figure 1b, d, f). As a result, the normalization of the larger event does not affect that of the lower-amplitude event, allowing PhaseNet to accurately detect both.

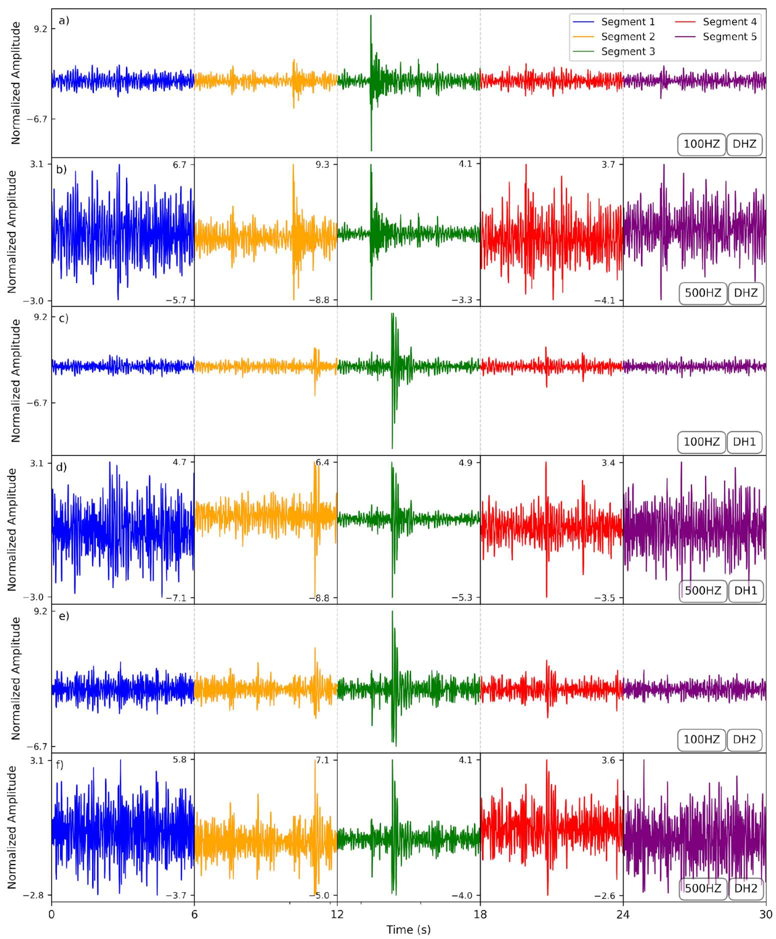


Figure 1- Three-channel microseismic waveforms from a 30-second window of TOC2ME data (station 1166, beginning at 2016-11-03 11:04:28). Panels (a, c, e) display the data resampled at 100 Hz, in which two closely spaced events occur at approximately 11 seconds (lower amplitude event) and 13.5 seconds within a single window. Panels (b, d, f) present the corresponding 500 Hz data segmented into 6-second (3001 data points) segments, with each segment normalized by itself, effectively isolating the two events.

After preprocessing the data, which included merging, detrending, and applying a bandpass filter (8-50 Hz), the first arrivals were picked using PhaseNet, with a probability threshold of 0.2 for both phases, from the Seisbench package—a toolbox for applying various phase-picking machine learning models to seismic data (Woollam et al., 2022). The detected arrivals were then associated using the Rapid Earthquake Association and Location (REAL) package (Zhang et al., 2019). The associated events were subsequently located using Hypoinverse, followed by relocation with HypoDD-dtct -(Klein, 2002; Waldhauser, 2001). The LOC-FLOW repository available on GitHub was used to implement the association and location steps (Zhang et al., 2022).

Results

Using the previously described workflow, we applied PhaseNet to the entire TOC2ME dataset, followed by association and event localization. A comparison of our results with the Eaton et al. (2018) and Igonin et al. (2020) catalogs is presented in Figure 2. The map in Figure 2b demonstrates that the spatial distribution of events detected by PhaseNet are highly concentrated in the areas where hydraulic fracturing occurred, aligning closely with seismicity distributions in the other two catalogs. However, the number of events detected by PhaseNet varies depending on the sampling rate of the input data, with a notable increase in detections when using 500 Hz data compared to 100 Hz data. Figure 2a showcases the comparative success rates of detection. When using 6-second input windows (500 Hz data), PhaseNet successfully detected and picked approximately 98% of the events in the Eaton et al. (2018) catalog and around 81% of the events in the Igonin et al. (2020) catalog. On the other hand, with 30-second input windows (100 Hz data), the detection success rates dropped to 85% for the Eaton et al. (2018) catalog and 50% for the Igonin et al. (2020) catalog. This reduction suggests that a higher sampling rate of the input data significantly enhances the ability of PhaseNet to detect microseismic events.

For the missed events in the 500 Hz dataset, a detailed review revealed that most had a low SNR. Many of these events were likely detected in the Igonin et al. (2020) and Eaton et al. (2018) catalogs using template-matching techniques, which are particularly effective in detecting low-SNR events that can be challenging for both automated methods and expert analysts. PhaseNet also detected a substantial number of new events compared to both other catalogs (Figure 2b). Notably, when using 500 Hz data, PhaseNet detected 3,015 additional events not present in the Igonin et al. (2020) catalog. This is particularly significant given that the Igonin et al. (2020) catalog contains the highest number of events (18,040) among the four previously published catalogs for this dataset.

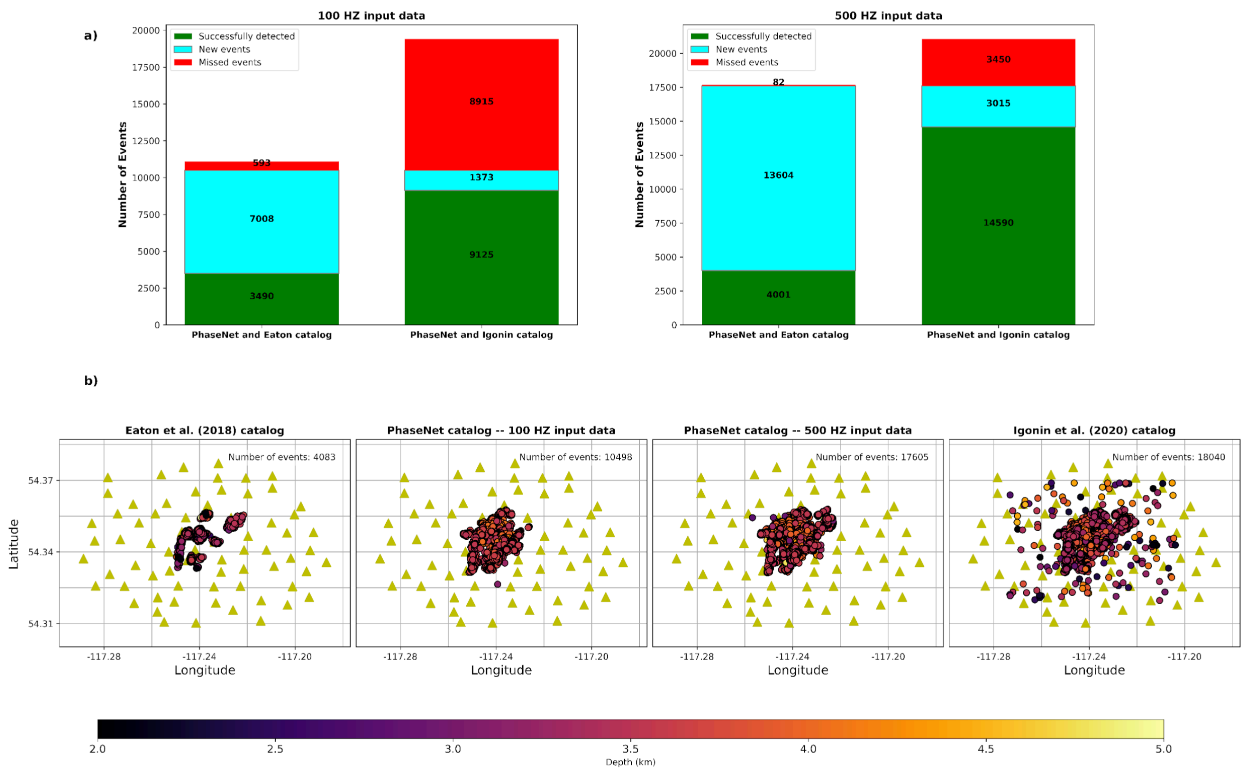
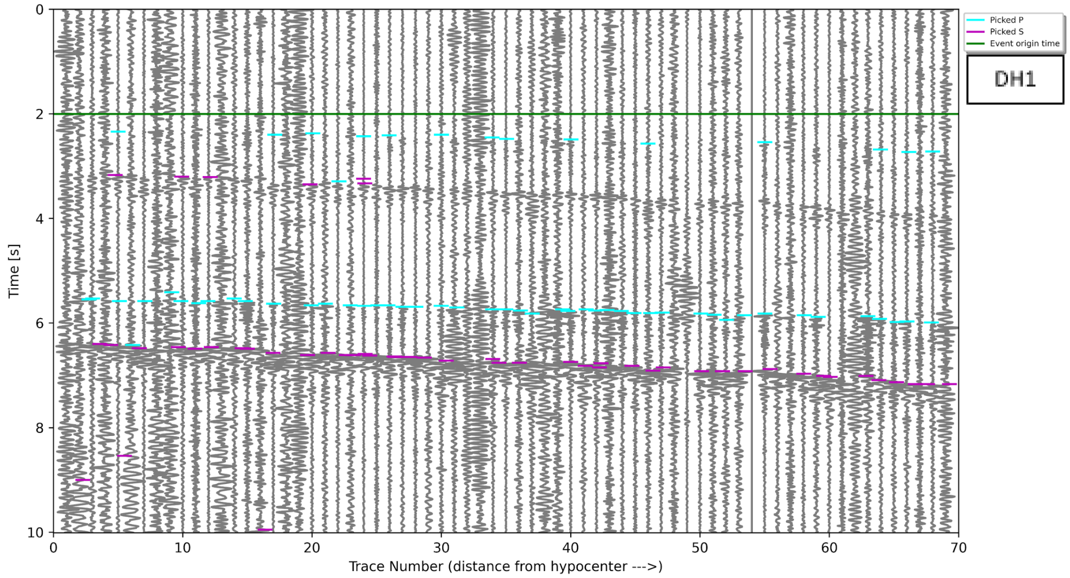


Figure 2-a) Comparison of PhaseNet-picked events with two published catalogs for the TOC2ME dataset. The left bar represents comparisons with the Eaton et al. (2018) catalog, while the right bar corresponds to comparisons with the Igonin et al. (2020) catalog. b) Maps of events from Eaton et al. (2018) (left), events detected by PhaseNet (middle), and the Igonin et al. (2020) catalog (right), color-coded by event origin depth.

The impact of changing the input window length from 30 s to 6 s is also illustrated in Figure 3. As shown, when the model was applied to the 30-s 100 Hz resampled data (Figure 3a, b), it struggled to detect the smaller amplitude event occurring before a larger-amplitude event within the same 30-second window. However, by retaining the original sampling rate of 500 Hz (resulting in 6-second windows), PhaseNet successfully detected both P- and S-wave arrivals for both events within the same window (Figure 3c, d). This underscores the significant advantage of using shorter input windows and highlights the robustness of this technique in processing microseismic data.

a)


Picked P
Picked S
Event origin time
DH1
Time [s]
Trace Number (distance from hypocenter --->)
0
2
4
6
8
10
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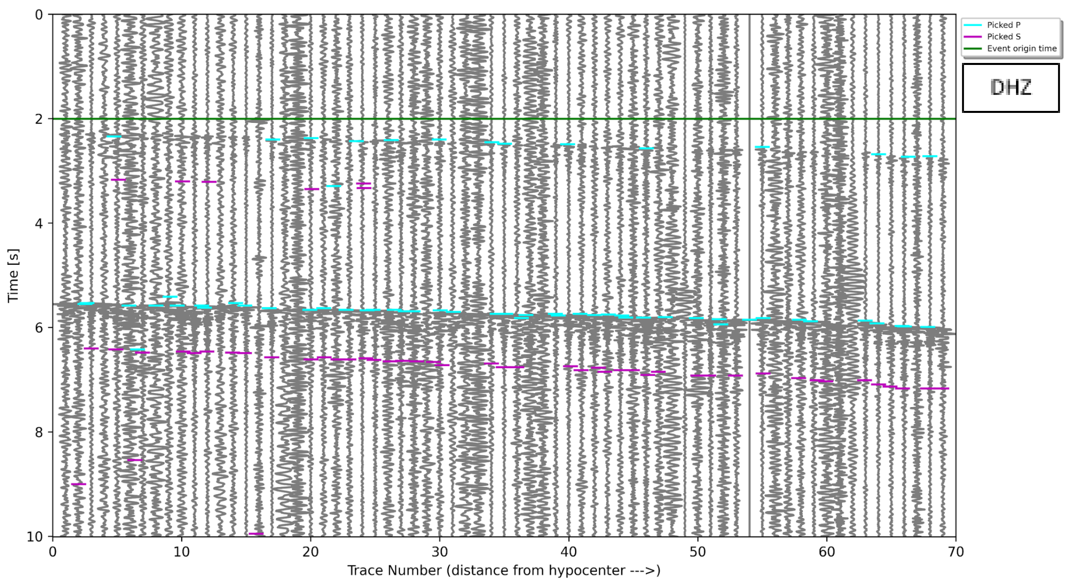
20
30
40
50
60
70

b)


Picked P
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Event origin time
DHZ
Time [s]
Trace Number (distance from hypocenter --->)
0
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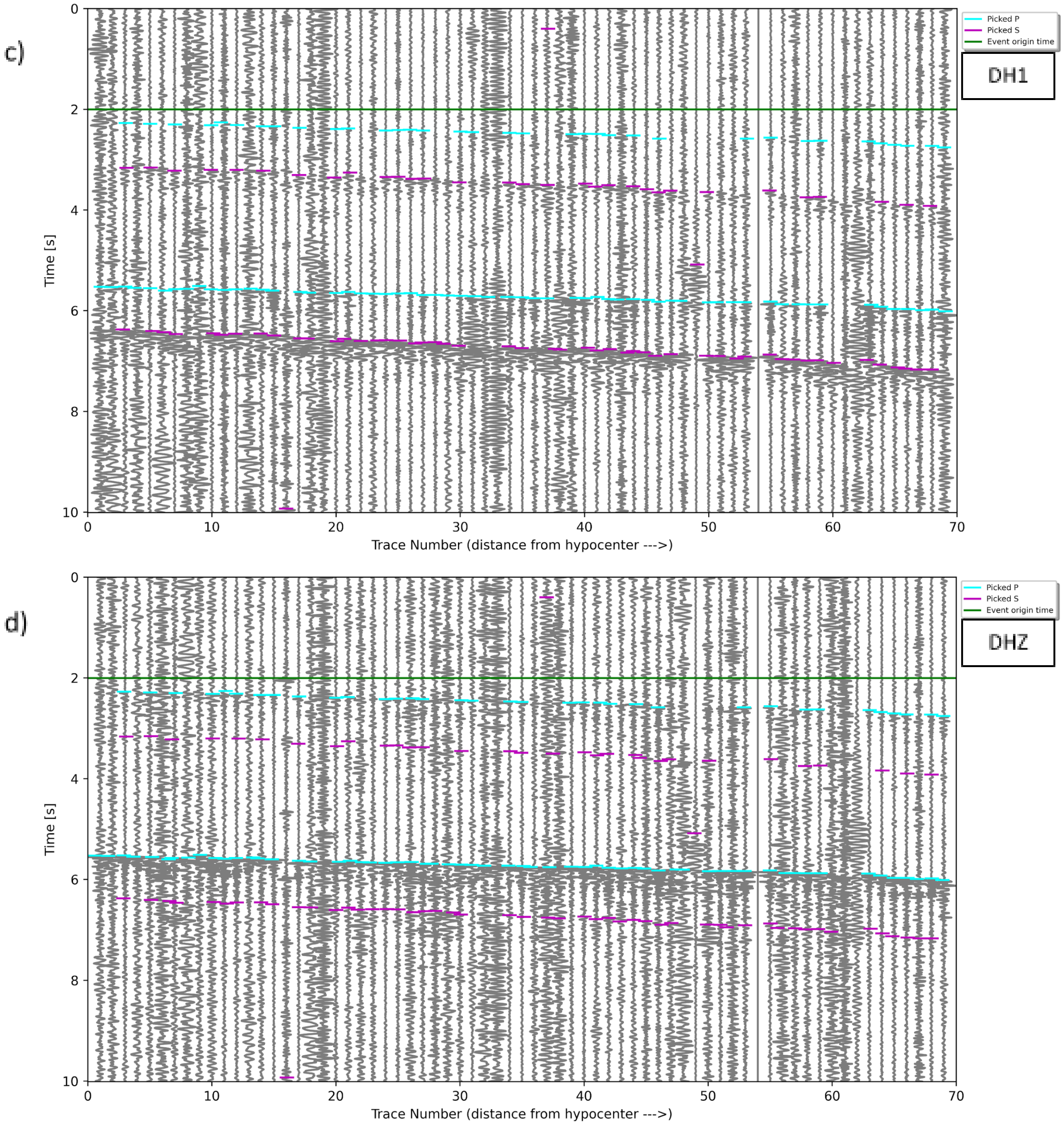

Figure 3- Microseismic data record sections showing the impact of input window length on event detection and phase-picking. For 30-sec 100 Hz input data (a, b), PhaseNet struggled to pick arrivals of multiple events. For 6-sec 500 Hz input data (c, d), PhaseNet successfully detected both P- and S-wave arrivals, highlighting the advantage of retaining the original sampling rate and using shorter input windows.

Conclusion

This research demonstrates that deep learning methods trained initially on earthquake data, such as PhaseNet, can be effectively applied to microseismic data, offering significant improvements in both accuracy and efficiency for signal processing compared to traditional automatic phase picking methods such as STA/LTA. Crucially, our findings reveal that retraining the models specifically for microseismic data is unnecessary if the input data are pre-processed to match the training conditions closely. In this study, we achieved this alignment by maintaining a higher sampling rate, effectively shortening the input window length and reducing the number of events in each analysis window, thereby addressing challenges posed by too many microseismic events in a 30-sec standard input window for PhaseNet. This adjustment enabled the model to perform exceptionally well in detecting P- and S-wave arrivals, even in complex scenarios with multiple events. These insights underline the importance of thoughtful data pre-processing to unlock the potential of existing deep learning models for microseismic applications, paving the way for more reliable and efficient microseismic monitoring.

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