Automatic Event Detection of Mining-Induced Microseismic Data based on PhaseNet: A Case Study of a Nickel-Copper Mine, Ontario

Sepideh Vafaei Shoushtari, Bernard Giroux

Centre Eau Terre Environnement, Institut National de la Recherche Scientifique

Summary

The underground extraction of mineral resources is frequently associated with induced microseismic events. To enhance operational safety and mitigate risks, continuous monitoring of mining-induced seismicity using a seismic network is a common approach. An effective monitoring system requires a detailed catalog of microseismic events, spanning low to high magnitudes, to assess how the rock mass responds to mining activities. Traditional methods of detecting low-magnitude events through manual picking or automated conventional methods are time-consuming and less accurate in comparison with Convolutional Neural Networks (CNNs) trained on large seismic datasets, which have shown improved capabilities in event detection and picking arrival phases from seismic data captured by regional networks.

In this work, we assess the effectiveness of PhaseNet, a deep CNN method for arrival-time picking, to identify the P- and S-wave arrivals of microseismic events induced by mining activities. The proposed mine, which conducts nickel and copper operations, experiences mining-induced earthquakes each year, creating risks for miners and infrastructure. Given the scarcity of high-quality, labeled microseismic datasets for such mining scenarios, a realistic three-component synthetic dataset is simulated through full waveform modeling.

The outcomes from the PhaseNet model trained on this simulated dataset indicate its success in handling noisy environments. This capability enables the detection of low-magnitude events in the mining setting that might be missed by conventional techniques. Tests conducted on real data across three different training scenario comprising training on real data, employing a pre-trained model, and retraining with both real and synthetic datasets demonstrate that the model retrained with synthetic and a less amount of real microseismic data provides the most accurate arrival time predictions, delivering reliable predictions for both P- and S-wave arrival times.

Method

Safety and risk management are crucial in the mining industry, especially underground, where geotechnical hazards like rock bursts pose serious threats (Gibowicz & Kijko, 1994). Mining-induced seismicity results from complex interactions between local stress and geological factors, often leading to sudden energy releases in rock masses. Accurate predictions of these hazards are challenging due to the intricacies of stress and fracture patterns. Seismic monitoring systems provide insights but struggle with precise rock burst timing.

Monitoring microseismicity involves event detection and phase picking, which are vital for understanding energy patterns and spatial distributions related to potential rock bursts. These insights aid in developing early warning systems (Feng et al., 2015). However, detection depends heavily on accurate arrival-time identification, and as data volume increases, managing this information becomes difficult. Identifying S-wave arrivals complicates matters further, as they can be obscured by P-wave interference. Accurate S-wave timing is essential for determining event locations and predicting ground motion (Akram, 2018). PhaseNet is a deep neural network initially designed for monitoring earthquakes, and a significant focus of this study is to evaluate its effectiveness for mining-related applications. It utilizes the U-Net architecture, which was originally conceived for image segmentation in the biomedical field (Ronneberger et al., 2015). PhaseNet has been adapted to work with seismic waveforms using one-dimensional (1D) inputs, allowing it to produce segmentations for the probabilities of P- and S-phases. The input to PhaseNet is a three-component seismic waveform, represented as a one-dimensional vector with three channels. This configuration yields three output channels, each indicating the likelihood that a particular data point belongs to one of three categories: P-arrival, S-arrival, or noise at each time step (Zhu & Beroza, 2019).

For data simulation and training the model, source parameters of multiple microseismic events are randomly generated. Their spatial coordinates are sampled from two probability density functions (pdfs): half from a uniform distribution within the mine and the other half aligned with the spatial velocity gradient, as shown in Figure 1. This alignment focuses on areas like stopes and orebodies that are more prone to induced seismicity.

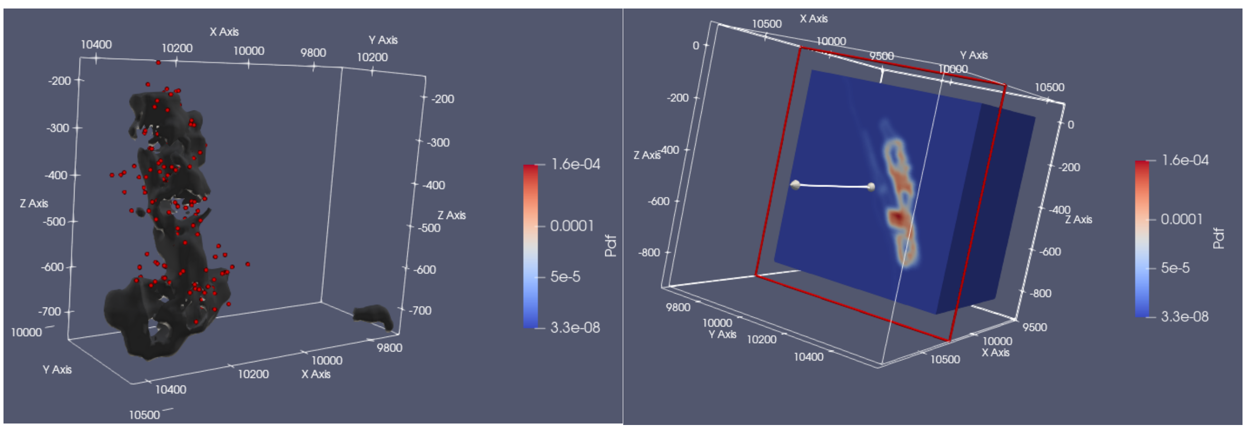

Figure 1. Left: Spatial gradient of the velocity model, right: Source positions in areas with high stresses within the velocity gradient.

Results

As illustrated in Figure 2, the plots present the performance of the trained model on synthetic seismograms from three distinct test datasets, all derived from the same seismic event but characterized by varying noise levels. In panels, we observe the predictions for P- and S-waves on synthetic data featuring $\log_{10}(\mathrm{SNR})$ values of 0.6 and 0.301, which correspond to white Gaussian noise conditions and the third panel showcases the model performance on dataset associated with colored noise.

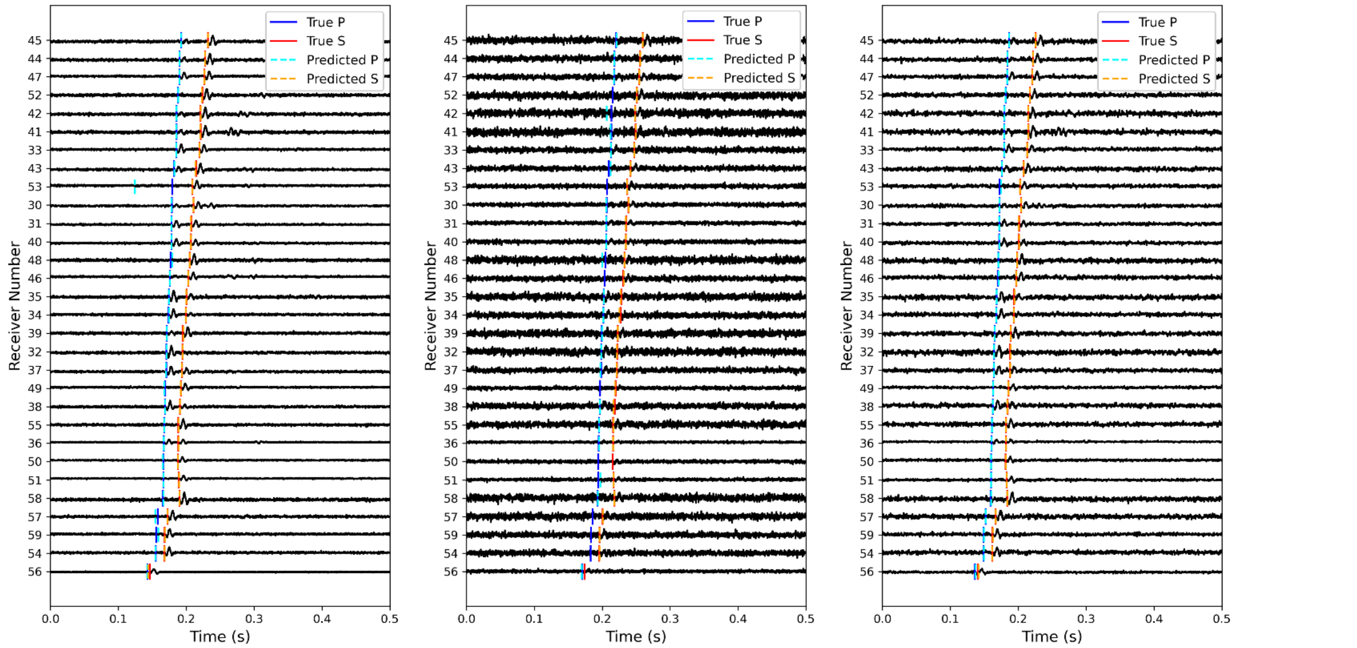

Figure 2. Performance of the trained model on synthetic microseismograms across three different test datasets derived from the same event, each exhibiting varying noise levels. The panels on the left and the middle, illustrate the P- and S-wave predictions on synthetic data with $log_{10}(SNR)$ values of 0.6 and 0.301 representing white Gaussian noise. The right panel illustrates the model performance on the dataset corresponding to colored noise.

In deep learning, model generalization is the ability of a trained model to perform well on new, unseen data, which is essential for real-world applications. To evaluate the generalization of a model trained on synthetic data, we test its performance on a portion of real seismograms. This real microseismic dataset includes events of different magnitudes captured by 6 uniaxial geophones, 26 triaxial geophones, and 39 accelerometers in the mine monitoring area. These instruments recorded both P- and S-waves, with the onset times determined by either an advanced automatic processing algorithm or experienced interpreters, all subjected to quality control. Three distinct strategies are employed to evaluate the influence of model pre-training on arrival-time estimations for the real dataset. The first strategy involves training PhaseNet only on the real dataset, utilizing quality-controlled arrivals to identify specific arrival patterns within the mine. While this method tailors the model to real-world data, its limitations may stem from the dataset size, quality, and diversity. To create a balanced training and validation dataset while fine-tuning the pre-trained model with synthetic data, careful labeling of P- and S-wave arrivals was conducted. The aim was to ensure that the distributions in both datasets reflected the true characteristics of real seismic data, maintaining proportionality between P- and S-wave events and preventing bias. The second and third scenarios both utilize a pre-trained model to enhance performance with real mining data. In the second approach, the model was initially trained on a synthetic dataset contaminated with high noise levels, then re-trained using both synthetic and real seismic data, ultimately fine-tuning it on the actual mining dataset. This process allowed the model to better adapt to real mining-induced seismic characteristics. In contrast, the third scenario used a pre-trained model that only underwent training on synthetic data without any further adjustment for real events.

The evaluation results present a comparison of three training methods, highlighting the effects of pretraining and synthetic data on model performance. In Scenario 2, the pre-trained model, initially trained on high-noise synthetic data and fine-tuned with real seismic data, achieves the highest accuracy, precision, recall, and F1-score for detecting both P-wave and S-wave arrivals. This indicates its strong generalization and robustness in various noise conditions. Meanwhile, Scenario 1 lacks the benefits of synthetic pretraining, resulting in lower accuracy. Scenario 3, trained solely on synthetic data, has a weak performance, struggling to adapt to real seismic patterns. These results highlight the importance of synthetic data for initial training and the need for real data in fine-tuning to enhance detection reliability in complex mining settings. PhaseNet predictions for randomly selected real data waveforms are displayed in Figure 3.

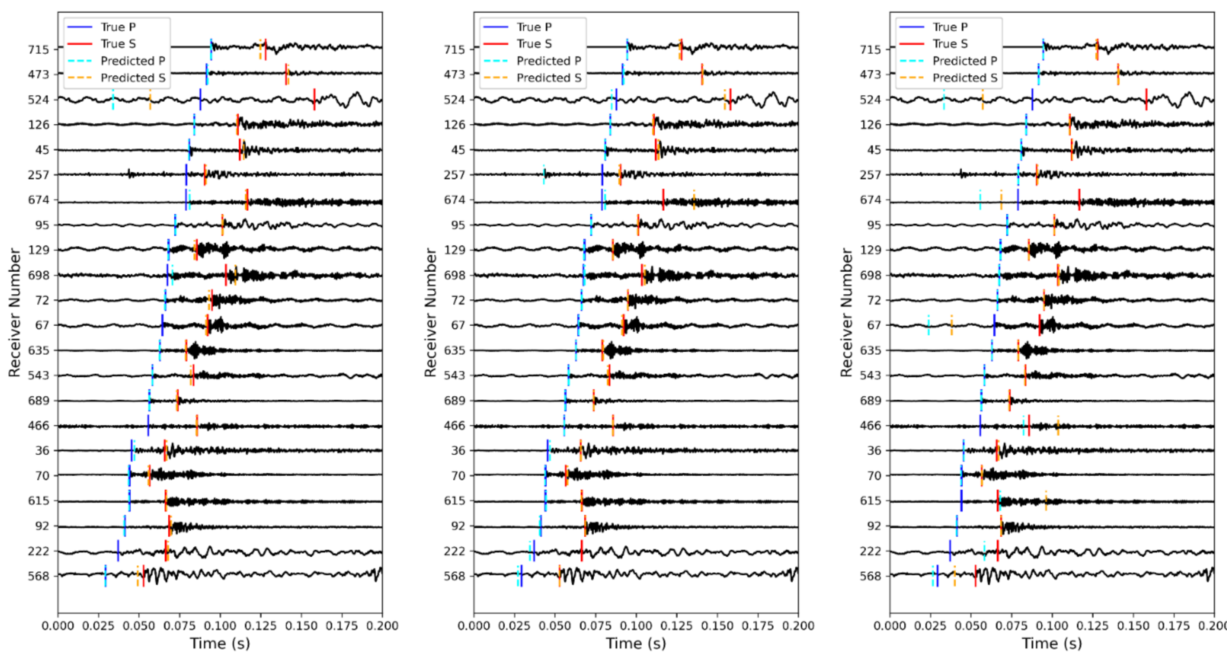

Figure 3. Performance of the trained models across the three scenarios on unseen real seismograms. The three panels display several waveforms received by true sensors with respect to the arrival times of P-waves: (a) Scenario 1, (b) Scenario 2, and (c) Scenario 3.

Conclusions

This study investigates the use of PhaseNet, a deep convolutional neural network, to detect microseismic events and pick seismic phases in a high-stress underground mine. The unique architecture of PhaseNet enables it to effectively identify occurrences of microseismic events.

The experimental results demonstrate that the trained model is skilled at locating low-magnitude events and offers a level of accuracy superior to conventional mining techniques (results not presented herein), which often overlook such events. Moreover, this neural network approach does not rely on data denoising or filtering, allowing for quicker processing of microseismic data. The model, trained on synthetic microseismograms, is also leveraged to develop a more robust and generalized predictor for arrival times in actual mine datasets.

Although there are differences in synthetic and actual microseismic signals and their level of noise, retraining the model with real data helps it adjust to these variations. This process fine-tunes PhaseNet to improve its predictive performance when applied to real mining data. By utilizing a small subset of real data comprising labeled microseismograms, the model learns the distinctive noise patterns of the actual dataset, resulting in more accurate detection of microseismic events on unseen data from the mine. Essentially, while initial training establishes a solid groundwork, retraining helps connect synthetic and real data, enhancing the model precision and reliability in real-world applications. This demonstrates the promise of incorporating advanced machine learning techniques into seismic data analysis for better monitoring of mining operations. Additionally, while PhaseNet was initially designed for seismological data, we took advantage of its architecture to effectively process and analyze passive seismic data collected from a specific mining site. Our approach involved customizing the model to recognize and interpret the unique characteristics of microseismic waveforms generated by mining activities, enabling event detection.

References

Akram, J. (2018). An application of waveform denoising for microseismic data using polarization–linearity and time–frequency thresholding. *Geophysical Prospecting*, *66*(5), 872-893.

Feng, G.-L., Feng, X.-T., Chen, B.-r., Xiao, Y.-X., & Yu, Y. (2015). A microseismic method for dynamic warning of rockburst development processes in tunnels. *Rock Mechanics and Rock Engineering*, *48*, 2061-2076.

Gibowicz, S. J., & Kijko, A. (1994). *An introduction to mining seismology*. Elsevier.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18,

Zhu, W., & Beroza, G. C. (2019). PhaseNet: a deep-neural-network-based seismic arrival-time picking method. *Geophysical Journal International*, *216*(1), 261-273.