GEOFIZIKA VOL. 42 2025

*DOI: https://doi.org/10.15233/gfz.2025.42.2*
*Original scientific paper*



# Research on applying deep learning technology to classify earthquakes and blasting events using a Lightweight Convolutional Neural Network

*Shaohui Zhou* [1], *Jian Li* [2], *Qijie Zhou* [3], *Yang Liu* [2], *Huilin Wang* [2], *Yu Wang* [1], *Chong Wang* [2], *Bing Lin* [2], *Han Zhang* [2], *Limei Peng* [2] *and Dongya Li* [2]

[1] Shandong Earthquake Agency, Ji Nan, China

[2] Hainan Earthquake Agency, Haikou, China

[3] Guangxi Earthquake Agency, Nanning, China

*Received 3 June 2024, in final form 1 February 2025*

This paper proposes a lightweight convolutional neural network model to identify the types of earthquake and blasting events quickly and accurately. Since an event is generally recorded by several stations, it is necessary to preprocess and classify the data based on the event beforehand. This ensures that different station waveforms of the same event do not appear in any two of the training sets, validation sets, and test sets. With the three-component waveforms recorded by stations after preprocessing as the input, the network model and hyperparameters are optimized by analyzing the average and variance in the accuracy and loss values of the verification set in the fivefold cross-validation, and the accuracy and loss curves in the training process. Finally, the classification results of all stations that achieve a certain signal-to-noise ratio for each event are taken as the output of this event type based on the principle that the majority prevails over the minority. This study uses 2,190 natural and blasting events recorded by the Hainan Seismic Network before August 2022, which includes 53,067 waveforms, to train and test the effectiveness of the model. Twenty percent of those events are selected randomly as the test set. The results showed that out of 438 randomly selected events, 427 were correctly identified, resulting in an accuracy rate of 97.48%. Specifically, the accuracy rate for seismic events was 95.59%, with a recall rate of 89.04%, while the accuracy rate for blasting events was 97.84%, with a recall rate of 99.18%. In conclusion, the convolutional neural network model proposed in this paper can rapidly and accurately identify natural and blasting types in Hainan.

*Keywords*: deep learning, classification, earthquake, blasting, CNN-convolutional neural network

## 1. Introduction

With the rapid development of digital seismic observation system technology in China, the density of stations has gradually increased, and the seismic monitoring capacity has significantly improved. At present, in addition to monitoring various natural earthquake events, the number of various non-natural events that can be monitored by the seismic network has also increased exponentially (Feng et al., 2017). Additionally, compared with natural earthquakes of the same magnitude, the source of nonnatural events is shallow, and strong tremors are often felt. In addition, most of them occur in densely populated areas, which are characterized by high intensity (Qian Qihu, 2014; Zhou Shaohui, et al. 2021; Li, et al. 2023a, 2023b). For example, the most influential non-natural earthquake event determined by experts in the world in recent years is the Pohang Mw5.4 earthquake in South Korea, which was caused by a local geothermal power station injecting water into the ground (Grigoli et al., 2018; Kim et al., 2018). After the official investigation results were released, the geothermal power plant and the Korean government faced enormous claims, and some people directly requested to deal with relevant personnel as man-made disasters.

Therefore, it is extremely important to determine the event type quickly and accurately after the seismic network has monitored various vibration events. In recent years, deep learning methods in artificial intelligence have developed rapidly, and a many researchers have introduced them into the seismology field, including automatic seismic phase identification (Perol et al., 2018; Sujun et al., 2021; Guo Huili et al., 2022), omission earthquake inspection and improvement of earthquake catalog (Yang et al., 2020; Zhao Ming et al., 2021; Zhu Jingbao et al., 2022), and earthquake prediction (Devries et al., 2018; Plaza et al., 2019; Asim et al., 2020). Additionally, some researchers have introduced deep learning algorithms into the vibration event type identification. For example, Linville et al. (2019) used the time-frequency maps of blast and earthquake recorded waveforms as input and used Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) to train event type determination for blast and earthquakes in the last five years in Utah, USA, with a final recognition accuracy of 98%. Zhou Shaohui et al. (2021) used the original 3-D waveforms recorded at the earliest five stations for earthquakes, blasting events, and collapse events as input. Four CNN structures were used for training, and the results showed that the recognition accuracy of all types of structures reached over 93% for both the training sets and test sets. Kong et al. (2022) proposed a method that combines deep learning with physics-based features to enhance the discrimination between earthquakes and explosions. The combination of these two approaches improved the generalization performance of the model, especially when applied to new regions. Koper et al. (2024) applied a spectral modeling workflow to classify small seismic events into earthquakes, explosions and collapses. The study found that models developed with a few physics-based waveform features can classify small seismic events with performance comparable to high-dimensional deep-learning models. Saad et al.(2024) proposed a capsule neural network guided by a compact convolutional transformer to discriminate between earthquakes and quarry blasts. The model first transforms the seismic waveforms into a time-frequency representation (scalogram) using the Continuous Wavelet Transform (CWT), which is then used as the input for the Capsule Neural Network, thereby achieving robust classification accuracy. The model achieved a testing accuracy of 97.31%, outperforming traditional deep learning models and demonstrating high generalization ability.

Each of the above studies has its own characteristics and has achieved good results by employing traditional machine learning or deep learning approaches. With various waveforms monitored by the station as input and relevant tags as output, they generate recognizers after training and learning a large quantity of data and finally achieve high accuracy recognition on the test set. However, most of the studies have performed artificial feature extraction on the input waveforms or calculated time-frequency spectra, resulting in the loss of some original waveform information, and due to the complexity of the recognition problem, the generalization ability of the classification model needs to be improved. As studies show that although the accuracy rate of a given group of data randomly divided into training sets and test sets after training can reach more than 93%, once the classification model is actually applied to the determination of the type of follow-up events in the same region, the recognition accuracy rate will drop significantly to 80.9% (Zhou et al., 2021). The reason for this kind of problem may be that the waveform data in the station unit are used as input during the training and testing of event waveforms, which easily leads to different station waveforms recorded in the same event. Some station waveforms are used as training sets, and some are used as test sets. That is, the recorded waveform of the same event is used as both training data and test data. In practical work, all recorded station waveforms of a new event are judged as the classifier input. This leads to the fact that the data selection in model training is not exactly the same as that in actual application, leading to the high accuracy of many researchers' models in training sets and test sets, and the accuracy will drop significantly once applied to actual work. For example, Gao et al. (2022) used a total dataset of 5000 waveforms composed of earthquake and blasting waveforms for deep learning training. The first 4,500 waveforms were used as training sets, while the remaining 500 waveforms were used as test sets. However, this can easily lead to different station waveforms recorded in the same event, with some station waveforms used as training sets and others as test sets. This setup potentially raises concerns about data leakage.

Therefore, to be closer to the earthquake rapid reports of actual event type determination and identification, realize the fast and efficient identification of natural and blasting events, and put them into practice, based on previous studies, this paper focuses on analyzing time-domain features of seismic waveforms

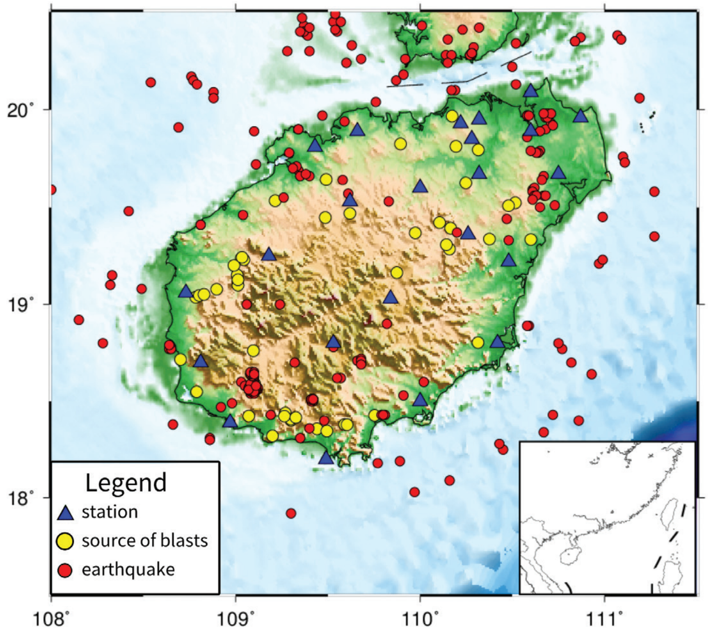


**Figure 1.** Basic overview of the study area.

of both earthquake and blasting recorded by the Hainan Seismic Network until August 2022. The dataset used for this research was recorded by the Hainan Seismograph Network. Hainan Island situated in the northwest of the South China Sea, covering an area of 33920 square kilometers. The Hainan island is abundant in blast, with quarries, iron mines, gold mines and other industrial activities serving as the main sources of blast (Fig. 1).

Based on previous studies, an elaborately designed lightweight convolutional neural network (CNN) model is constructed for analysis. For each event, all three-component signals recorded by various stations with a sufficient signal-to-noise ratio are used as inputs to the model, while the event type serves as the output. During the training process, the generalization ability of the model is enhanced by employing dynamic data loading and random data augmentation techniques. A 5-fold cross-validation is employed to assess the accuracy and loss curve variations between the validation and training sets. This iterative process involves fine-tuning the network architecture and hyperparameters to achieve the optimal classification model. Model recognition performance is evaluated both on a station waveform basis and an event basis. It is worth noting that to avoid having the same event's station waveform appear in the training, validation, and test sets, a data preprocessing step is performed in advance, categorizing the data on an event basis.

## 2. Method and principle

### *2.1. Data preprocessing*

When evaluating the accuracy of a model using deep learning, it is common to shuffle the data and split it into training, validation, and test sets. However, this approach is not applicable to earthquake data. Evaluating the model using the conventional deep learning approach would lead to a "cheating" issue. This is because, in general, an earthquake event is recorded by multiple seismic stations, and each recording can be considered a sample. Waveforms recorded from the same event by different seismic stations exhibit a certain level of similarity. The closer the two stations are in proximity, the higher the waveform similarity. This implies that if waveforms from the same event recorded by different stations are included in either the training set, validation set, or both the training and test sets, it will introduce certain errors.

If there is a scenario where multiple waveforms from the same event are concurrently included in both the training and test sets, it implies that the network has been exposed to the waveforms present in the test set during the learning process. As a consequence, this exposure may overestimate the accuracy, thereby yielding misleading outcomes. If multiple waveforms from the same event are present simultaneously in both the training and validation sets, it can result in the accuracy-epoch curve and loss-epoch curve of the training set being closely aligned. However, during the testing phase, the test set accuracy may be notably low. This discrepancy indicates a clear case of overfitting.

Such outcomes would not align with the principles and rigor expected in scientific research and should be avoided to maintain experimental design integrity and result validity. The data undergo preprocessing classification based on events prior to the preprocessing stage to avoid accuracy rate distortion in the model results caused by waveforms from the same event being recorded by different stations in the training set, verification set, or test set.

The data are divided into training, verification, and test sets based on events. Then, the set comprising the training set and verification set is randomly split into 5 subsets. To ensure valid signals as input for the CNN, the waveforms from triggered seismic and blasting event stations undergo the following preprocessing steps:

(1) Waveform truncation: Based on the arrival time of different seismic phases in the event waveform, the waveform signal is truncated at the station level, with a length of 9,000 points, starting 30 seconds before the arrival time of the seismic phase.

(2) Detrend: The detrend operation is applied to the truncated waveforms.

(3) Filtering: A fourth-order Butterworth high-pass filter was applied to the signal with a cutoff frequency of 2 Hz.

(4) Normalization: the waveform data are uniformly scaled and mapped to the range of –1 to 1.

(5) Initial machine automatic filtering: calculate the signal-to-noise ratio of various waveforms and apply a threshold to filter out waveforms.

(6) Manual final confirmation: after filtering, the waveforms of all stations shall be separately plotted in batches and checked manually to remove the waveforms of stations with abnormal waveforms.

### *2.2. Convolution neural network model*

Figure 2 shows the CNN model for waveform recognition. The model consists of three parts: the input, feature extraction, and output layers. Three-component seismic data with 9,000 sampling points in length, after normalization processing, are input into the network structure through the input layer. The feature extraction layer consists of three convolution layers, three maximum pooling layers, one dropout layer, and two fully connected layers. The activation function used in all convolution layers of the feature extraction layer is ReLU. The first fully connected layer uses the ReLU activation function, while the second fully connected layer uses the softmax activation function. To prevent overfitting, this model includes a dropout layer that randomly "discards" certain nodes, thereby

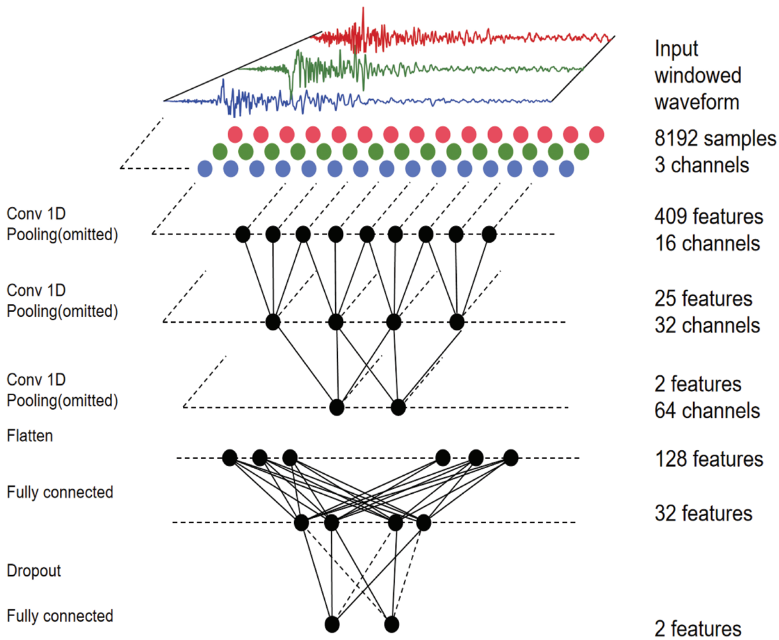


**Figure 2.** Convolutional neural network model.

enhancing the model's generalization ability. Finally, the CNN model produces 18,562 trainable parameters. The output layer is a sequence with a length of 2. Following the input layer and the feature extraction layer, the output layer produces a vector of length 2. A value of 1 in the first bit indicates blasting, while a value of 1 in the second bit indicates an earthquake.

### *2.3. Model training and parameter adjustment*

The CNN model is trained to accurately classify real event types in earthquake quick report tasks. After data preprocessing, the waveform is divided into training, validation, and test sets based on event units. The combined training and validation set is trained using fivefold cross-validation, which involves randomly dividing the set into five subsets and performing five iterations of training. One subset is chosen as the validation set in each iteration, while the remaining four subsets are used as the training set. The average accuracy and loss values from the five iterations are used to optimize the network structure and hyperparameters, considering the training process's loss and accuracy curves. Once the hyperparameters are tuned to their optimal values, the test set is used to objectively evaluate the network's performance.

Figure 3 presents the primary data processing framework of this study, with the preprocessing process omitted due to space constraints. It comprises the processing flow for the training set, verification set, and test set. These three components employ a consistent input method involving the labeling of waveforms corresponding to each event, shuffling the order of labeled waveforms,

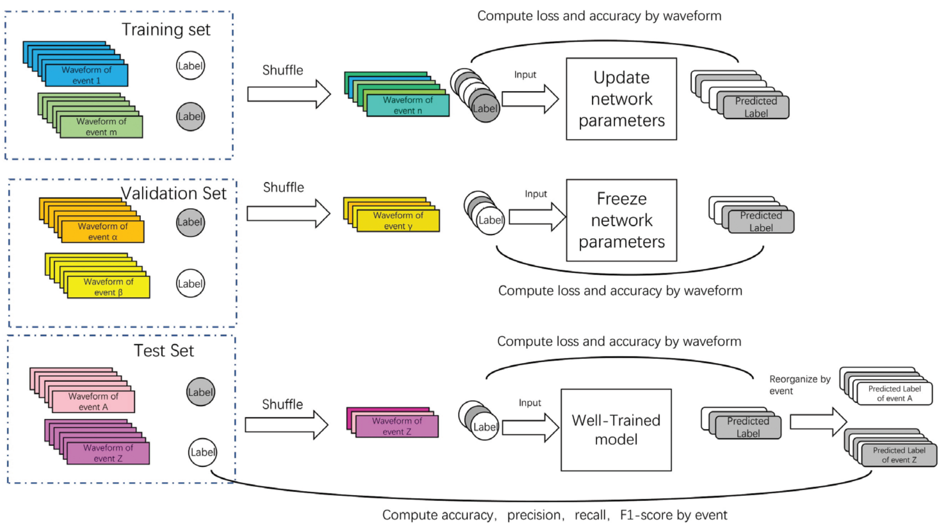


**Figure 3**. Flow chart of algorithm data in this paper.

grouping 128 waveforms as input to the network, performing forward propagation to generate predicted labels, and computing the cross-entropy loss value and accuracy using the predicted and actual labels.

An important aspect of the training set processing is that it includes backpropagation and parameter updates, involving the use of all input waveforms for one training epoch. After each epoch, the verification set waveforms are input into the network following the same procedure. Once all verification sets are processed, the cross-entropy loss value and accuracy can be calculated using the predicted labels and corresponding input waveform labels. Contrasting the verification set, the test set selects the final trained model. The predicted labels for each event in the test set are organized as a new set based on the event, integrating the prediction results from each station waveform to obtain the final prediction value. Subsequently, the accuracy, precision, recall, and F1 score are computed based on the predicted values and ground truth labels for each event in the test set. Notably, hot encoding is applied to convert the ground truth labels into a unique representation, while the prediction labels are in the form of a 2-bit array generated through the softmax layer.

During each training epoch, the data are randomly truncated into waveforms with a length of 9,000 points. There is a 30% probability of data augmentation. Data augmentation encompasses randomly translating specific areas of the data and introducing Gaussian noise with a fixed signal-to-noise ratio. This technique allows for the augmentation of seismic data, mitigates overfitting, and enhances the model's generalization capability.

The model training process is illustrated in Fig 4, where the solid black line represents the training set, and the red line represents the validation set. As the number of training iterations increases, the trends in accuracy and cost function (loss) for both the training and validation sets closely align. Accuracy gradually

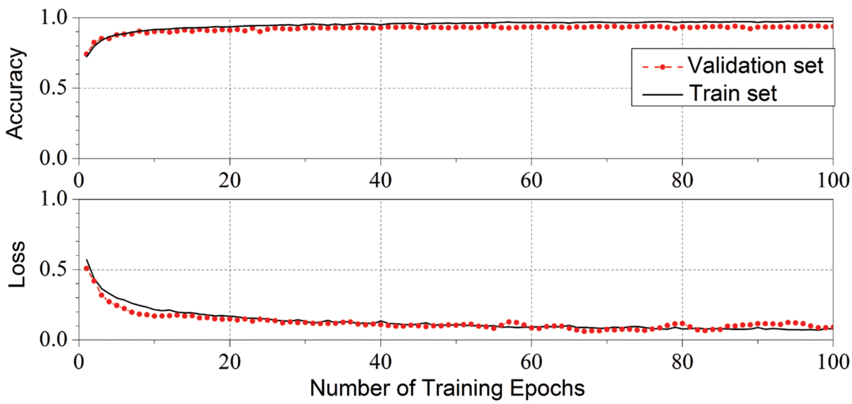


**Figure 4**. The process of model training.

rises with increasing training iterations, approaching 90%, ultimately stabilizing around a certain value. Simultaneously, the loss curve rapidly descends and eventually stabilizes at a relatively low value, ceasing to fluctuate further. Throughout the training process, this study employs 5-fold cross-validation based on accuracy and loss curves to assess the model's performance. This approach allows for the evaluation of different network architectures and hyperparameters, ultimately determining the optimal network model.

## 3. Data

This paper utilizes all natural earthquake and blasting events recorded by the Hainan Seismic Network Center prior to August 2022 as training and testing samples. A total of 438 events, proportionally representing the earthquake and blasting in the dataset, are randomly selected as the test set, while the remaining events constitute the training and validation sets. The training set undergoes evaluation using a fivefold cross-validation method.

These events were observed by 24 stations. The sampling rate of the waveform recorded by each station is 100. The waveforms recorded include three components: vertical, east–west, and north–south. Typical waveforms for earthquakes and blasting are shown in Fig. 5. It is evident that there are significant differences in waveform characteristics between the two types of events. For instance: ① Natural earthquakes exhibit well-developed S-waves, while blasting events show less pronounced S-wave development. ② The vertical component P-wave amplitudes for natural earthquakes are significantly smaller than those for blasting events. Therefore, it is possible to differentiate between event types by training a CNN model to learn the differences in waveform characteristics between natural earthquakes and blasting events.

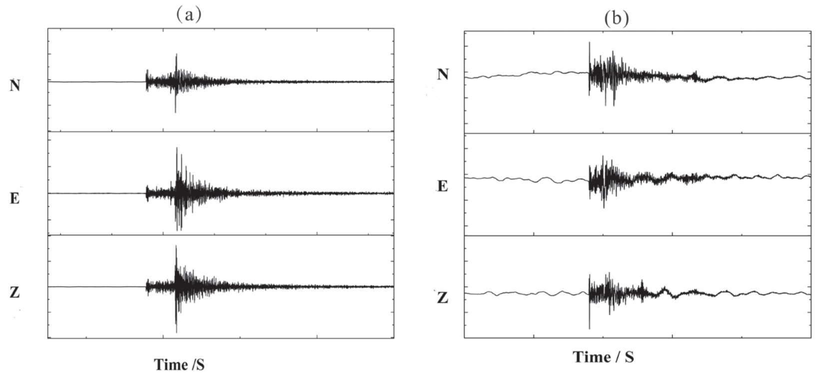


**Figure 5**. The waveform recording of blasting and earthquake. (a) The waveform recording of earthquake. (b) The waveform recording of blasting.

The training dataset consists of a total of 1,752 events, including 292 earthquakes and 1,460 blasting events. For each event, a matrix composed of three-component data from each station is used as a training sample, resulting in a total of 14,155 training samples, with 4,068 being earthquake samples and 10,087 being blasting samples. The test dataset includes a total of 438 events, consisting of 73 earthquakes and 365 blasting events. Similarly, for each event in the test dataset, a matrix of three-component data from each station is used as a test sample, resulting in a total of 3,534 test samples, with 976 being earthquake samples and 2,558 being blasting samples.

## 4. Training results and model evaluation

To assess the discriminative performance of the deep learning CNN proposed in this study during real-time operations in a digital seismic network, a test set comprising 3,534 station waveforms from 438 events was randomly selected for evaluation. The model's identification effectiveness was assessed separately at the waveform and event levels. Specifically, the evaluation metrics employed include the confusion matrix, precision rate, recall rate, and F1 score to determine the model's accuracy. In our study, earthquakes or blasts are labeled as "positive" events, while others are "negative". Precision tells us how many of the events predicted as earthquakes/blasts are actually earthquakes/blasts. It measures the model's ability to avoid false alarms. Recall indicates how many of the real earthquakes/blasts the model successfully detects. It reflects the model's ability to miss as few true events as possible. Accuracy is the overall proportion of correct predictions (both positives and negatives) made by the model. F1 Score combines Precision and Recall into a single metric by calculating their harmonic mean. It helps balance the trade-off between avoiding false alarms (Precision) and capturing all true events (Recall). A higher F1 Score means the model performs well in both aspects.

The test set consisted of 3,534 waveforms, with 976 representing natural earthquake events and 2,558 corresponding to blasting events. Table 1 shows the confusion matrix for waveform-level identification of earthquakes and blasts, with each row indicating the actual event count. Table 2 shows the precision rate, recall rate and F1 score of the model recognition in the waveform unit. Based on the data from Tabs. 1 and 2. Overall 819 seismic waveforms and 2552 blasting waveforms were correctly identified in the test set. Among them, 36 blasting waveforms are identified as earthquakes, and 157 seismic waveforms are identified as explosions. The accuracy rate for the blasting waveform is 94.14%, with a recall rate of 98.59%. For seismic waveforms, the accuracy rate is 95.79%, while the recall rate is 83.91%. The overall comprehensive recognition accuracy is 94.54% (Tab. 2). These results indicate that the CNN model developed in this study can rapidly and accurately classify the waveform type—whether it is a natural earthquake or a blast—at an individual station level.

*Table 1. Confusion matrix of earthquake and blasting identification results of the model in waveform.*

| | Blasting (predicted) | Earthquake (predicted) |
|---|---|---|
| Blasting (true) | 2,522 | 36 |
| Earthquake (true) | 157 | 819 |

*Table 2. Precision, recall rate, and F1-score of earthquake and blasting identification results of the model in waveform.*

| | Precision | Recall | F1-score |
|---|---|---|---|
| Blasting | 0.9414 | 0.9859 | 0.9631 |
| Earthquake | 0.9579 | 0.8391 | 0.8946 |

In the process of determining event types, collective observations from multiple stations rather than individual station waveforms are used. Thus, the model developed in this study is evaluated for its effectiveness in event-based type identification. During the event-based assessment, the waveforms from all corresponding stations that meet a certain signal-to-noise ratio for the event are individually identified. The principle of majority agreement is then utilized to determine the event type. Among the 438 events, there were 73 natural earthquakes and 365 blasting events. Table 3 shows the confusion matrix of the identification results of natural earthquakes and blasting in the event-based test set, while Tab. 4 displays the identification accuracy, recall and F1 score of the model in the same test set. The results indicate that out of the 365 blasting events, 362 were correctly identified, and among the 73 natural earthquakes, 65 were correctly identified. Eight natural earthquakes were misclassified as blasts, and three blasting events were mistakenly identified as earthquakes. The accuracy rate for blasting events was 97.84%, with a recall rate of 99.18%. For natural earthquakes, the accuracy rate was 95.59%, with a recall rate of 89.04%. Overall, the comprehensive recognition accuracy reached 97.49%. These findings demonstrate that the CNN model con-

*Table 3. Confusion matrix of earthquake and blasting identification results of the model in event.*

| | Blasting (predicted) | Earthquake (predicted) |
|---|---|---|
| Blasting (true) | 362 | 3 |
| Earthquake (true) | 8 | 65 |

*Table 4. Precision, recall rate, and F1-score of earthquake and blasting identification results of the model in events.*

| | Precision | Recall | F1-score |
|---|---|---|---|
| Blasting | 0.9784 | 0.9918 | 0.9850 |
| Earthquake | 0.9559 | 0.8904 | 0.9220 |

structed in this study can rapidly and accurately identify the types of natural earthquakes and blasting events in an event-based context.

It is worth noting that the misidentification of events occurred primarily in cases where waveform features were ambiguous, particularly during events characterized by waveform superposition, such as multiple events occurring within an extremely short time frame. Such instances of multiple event superposition are relatively rare. When multiple events occur within an extremely short time span, the waveforms recorded at observation stations overlap, leading to varying degrees of distortion in their original waveform characteristics. As a result, the waveforms lose their distinctive features. Figure 6 illustrates waveform recordings from observation stations during an event on August 29, 2021, where a blasting event overlapped with a seismic event. In cases of waveform overlap, it is challenging to discern two distinct events from the perspective of a single station, and the overall waveform closely resembles that of an earthquake. Figure 7 shows waveform recordings from observation stations during a double blasting event on August 10, 2021, where again, the overall waveform closely resembles that of an earthquake. For such events, relying solely on theoretical waveform characteristics is insufficient for determining the event type. In practice, a combination of on-site investigation and manual verification is often necessary. Ad-

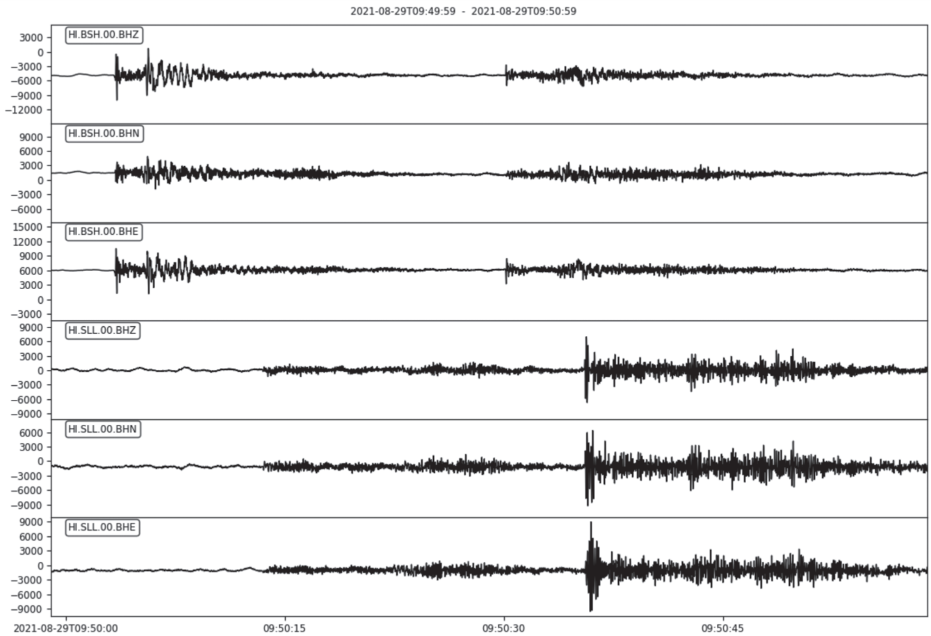


**Figure 6.** Waveform recordings of superimposed seismic events following a blast on August 29, 2021.

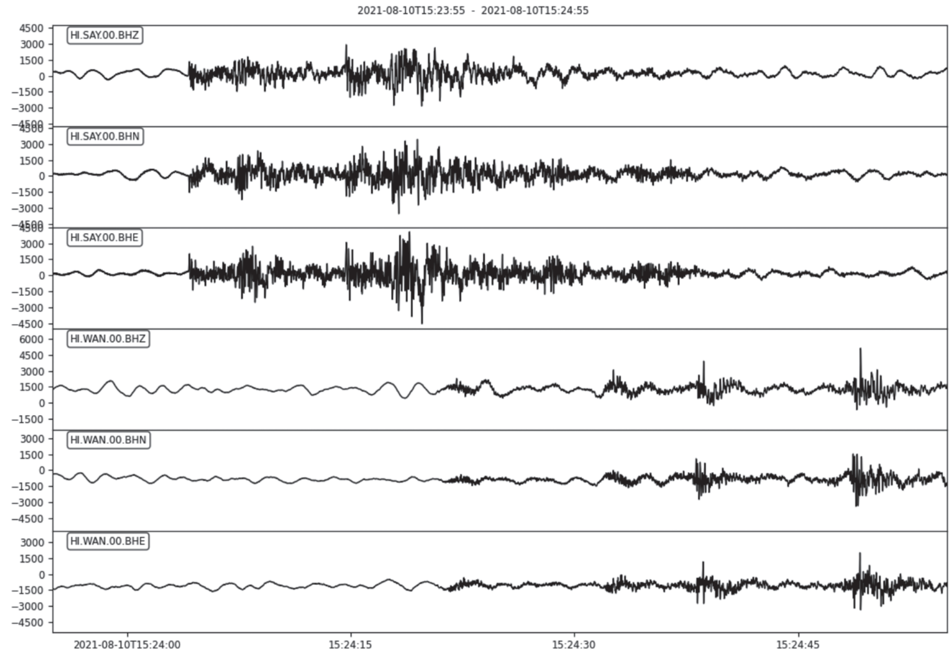


**Figure 7.** Waveform recordings of double blast events on August 10, 2021.

ditionally, it is possible that the reason for misidentification in such cases may also be due to the rarity of these situations, resulting in an insufficient number of samples available for model training.

Compared to recognition network models constructed by other researchers (Tab. 5), the CNN model built in this study exhibits an overall accuracy that is only 0.51% lower than that of the model by L. Linville (2019). However, due to cases of misidentification caused by the presence of superimposed multiple events in the events identified in this study, when excluding such events, the recognition rate of our model surpasses the other three models (achieving an overall accuracy of up to 98.4%). Moreover, the blasting event recognition accuracy in our model is the highest, while the recognition accuracy for natural

*Table 5. Model accuracy comparison.*

| Model | Accuracy (earthquake) | Accuracy (blasting) | Overall accuracy |
|---|---|---|---|
| L Linville (2019 CNN) | 99% | 95% | 98% |
| REN T (2019 bagging) | 80% | 91.3% | 86.62% |
| Yue et al. (2023 7-layer CNN) | 97.50%, | 91.35% | 94.438% |
| This paper | 97.84% | 95.59% | 97.49% |

earthquakes is not significantly different from the CNN models constructed by other researchers. This is primarily attributed to preprocessing the data based on events rather than having the same event's station waveform records appear in both the training, validation, and test sets. In this preprocessing approach, the input consists of three-component signals from preprocessed event station records. This method, to some extent, improves the network model precision by leveraging the mutual feature constraints from multiple stations, enabling the model to learn more accurate event characteristics during training.

## 5. Discussion and conclusion

(1) Earthquakes and blasting exhibit certain differences in waveform characteristics. This study designed a lightweight convolutional neural network (CNN) model that accounts for seismic signal features to address the event type recognition problem. We employed a dynamic data loading approach for preprocessing and input, which allows data to be loaded as needed during the training process. In addition, by incorporating random data augmentation through dynamic loading, we can enhance the generalization ability of the model, while also reducing the computational memory requirements of deep learning models. Furthermore, we performed event-based data preprocessing in advance using preprocessed three-component signals from event station records as input. This method, to some extent, enhances the accuracy of the network model by leveraging the mutual feature constraints from multiple stations. It enables the model to learn more precise event characteristics during training, thereby aligning more closely with the practical work of event type recognition in routine seismic network monitoring. This forms the basis for a practical technical system.

(2) We selected all earthquake waveforms recorded by the Hainan Seismic Network until August 2022, encompassing both natural earthquakes and blasting events, as the subjects of our study. For each event, three-component signals from all stations with a sufficient signal-to-noise ratio were used as input, with event type as the output for model training. During the training process, we continually optimized the network model and hyperparameters by analyzing metrics such as accuracy and loss curve variations between the validation and training sets in a 5-fold cross-validation setup. This iterative process aimed to obtain the optimal classification model. Subsequently, a test set comprising 976 earthquake samples and 2558 blasting samples was randomly selected for evaluation. The model's recognition performance was assessed both on a station waveform basis and an event basis. The results indicated that, compared to recognition network models constructed by other researchers, our model achieved the highest recognition accuracy.

(3) Our method cannot provide accurate event type determination in cases where waveforms from multiple types of events are superimposed, especially when multiple events occur within an extremely short time frame. This limita-

tion primarily arises from the fact that when multiple events occur within such a brief time period, the waveforms recorded at observation stations overlap, leading to varying degrees of distortion in their original waveform characteristics. Consequently, the waveforms lose their original distinctive features. Furthermore, our model cannot accurately identify such cases, which may also be attributed to the rarity of these situations, resulting in an insufficient number of samples for training. Consequently, the model cannot learn the accurate waveform characteristics of such events. Therefore, for rare events where certain waveform features are disrupted, our model faces certain difficulties in event type determination. Combining traditional event feature recognition methods, such as P-wave initial direction and waveform duration, may offer the potential for improved recognition performance in such cases.

In conclusion, the natural earthquake and blasting classification model based on convolutional neural networks proposed in this study has shown promising results on the dataset from Hainan. The next steps involve not only increasing the training data volume from other regions while maintaining label accuracy but also devising more intelligent waveform selection procedures to enhance the model's generalization performance, enlarging the pool of available training waveforms and employing other methods. These measures improve the model's recognition accuracy. Additionally, it may be beneficial to explore combining traditional event feature recognition methods during model training to achieve better event type recognition results.

*Funding statement* – This study was funded by National Natural Science Foundation of China (42474189), and the Science and Technology InnovationTeam of Shandong Earthquake Agency (TD202404, TD202405). Additionally, this research was supported by the Hainan Provincial Natural Science Foundation of China (Project No: 422QN429) for the project 'Crustal Shear Wave Attenuation Tomography in North Hainan Island and Offshore Areas.

## References

Asim, K. M., Moustafa, S. S. R., Niaz, I. A., Elawadi, E. A., Iqbal, T. and Martínez-Álvarez, F. (2020): Seismicity analysis and machine learning models for short-term low magnitude seismic activity predictions in Cyprus, *Soil Dyn. Earthq. Eng.*, **130**, 105932, https://doi.org/10.1016/j.soildyn.2019.105932.

DeVries. P. M. R., Viégas, F., Wattenberg, M. and Meade, B. J. (2018): Deep learning of aftershock patterns following large earthquakes, *Nature*, **560**(7720), 632–634, https://doi.org/10.1038/s41586-018-0438-y.

Feng, L. and Xiang, L. (2017): Challenges and research prospects of induced earthquakes, *Recent Developments in World Seismology*, **47**(5), 11–15.

Gao, Y., Yin, X. and Li, S. (2022): Automatic recognition of earthquake and blasting events based on deep learning, *J. Geodesy Geodyn.*, **42**(4), 426–430.

Grigoli, F., Cesca, S., Rinaldi, A. P., Manconi, A., Lópezt-Comino, J. A., Clinton, J. F., Westaway, R., Cauzzi, C., Dahm, T. and Wiemer, S. (2018): The November 2017 *M*w 5.5 Pohang earthquake: A possible case of induced seismicity in South Korea, *Science*, **360**(6392), 1003–1006, https://doi.org/10.1126/science.aat2010.

Guo, H. L., Chang, L. J., Lu, L. Y., Wu, P. P., Lü, M. M. and Ding, Z. F. (2022): High-resolution earthquake catalog for the focal area of the Qinghai Madoi MS7.4 earthquake based on deep-learning phase picker and dense array, *Chinese J. Geophys.-Ch.*, **65**(5), 1628–1643 (in Chinese), https://doi.org/10.6038/cjg2022P0863.

Huang, R., Zhu, L., Encarnacion, J., Xu, Y., Tang, C.-C., Luo, S. and Jiang, X. (2018): Seismic and geologic evidence of water-induced earthquakes in the Three Gorges Reservoir region of China, *Geophys. Res. Lett.*, **45**, 5929–5936, https://doi.org/10.1029/2018GL077639.

Kim, K. H., Ree, J. H., Kim, Y., Kim, S., Kang, S. Y. and Seo, W. (2018): Assessing whether the 2017 *M*w 5.4 Pohang earthquake in South Korea was an induced event, *Science*, **360**, 1007–1009, https://doi.org/10.1126/science.aat6081.

Kong, Q., Wang, R., Walter, W. R., Pyle, M., Koper, K. and Schmandt, B. (2022): Combining deep learning with physics based features in explosion - Earthquake discrimination, *Geophys. Res. Lett.*, **49**(13), e2022GL098645, https://doi.org/10.1029/2022GL098645.

Koper, K. D., Burlacu, R., Armstrong, A. D. and Hermann, R. B. (2024): Classifying small earthquakes, explosions and collapses in the western United States using physics-based features and machine learning, *Geophys. J. Int.*, **239**(2), 1257–1270, https://doi.org/10.1093/gji/ggae316.

Linville, L., Pankow, K. and Draelos, T. (2019): Deep learning models augment analyst decisions for event discrimination, *Geophys. Res. Lett.*, **46**(7), 3643–3651, https://doi.org/10.1029/2018GL081119.

Li, J., Jiang, H. and Wang, Q. (2023): Crustal attenuation structure of the Tianshan tectonic belt and its spatiotemporal variations, *Front. Earth Sci.*, **11**, 1094151, https://doi.org/10.3389/feart.2023.1094151.

Li, J., Gao, Y. and Zhou, S. (2023): Upper crust anisotropy of the 2020 Jiashi MS 6.4 earthquake, *Front. Earth Sci.*, **11**, 1160676, https://doi.org/10.3389/feart.2023.1160676.

Perol, T., Gharbi, M. and Denolle, M. (2018): Convolutional neural network for earthquake detection and location, *Science Advances*, **4**(2), e1700578, https://doi.org/10.1126/sciadv.1700578.

Plaza, F., Salas, R. and Nicolis, O. (2019): Assessing seismic hazard in Chile using deep neural networks, in: *Natural Hazards – Risk, Exposure, Response, and Resilience*, edited by Tiefenbacher, J. P. IntechOpen Limited, London, https://doi.org/10.5772/intechopen.83403.

Qian, Q. (2014): Definition, mechanism, classification and quantitative forecast model for rockburst and pressure bump, *Rock and Soil Mechanics*, **35**(1), 1–6.

Ren, T., Lin, M. N., Chen, H. F., Wang, R. R., Li, S. W., Liu, X. Y. and Liu, J. (2019): Seismic event classification based on bagging ensemble learning algorithm, *Chinese J. Geophys.-Ch.*, **62**(1), 383–392 (in Chinese), https://doi.org/10.6038/cjg2019M0380.

Saad, O. M., Soliman, M. S., Chen, Y., Amin, A. A. and Abdelhafiez, H. E. (2024): Capsule neural network guided by compact convolutional transformer for discriminating earthquakes from quarry blasts, *Seismol. Res. Lett.*, **95**, 320–328, https://doi.org/10.1785/0220230101.

Su, J., Wang, W., Zhang, L. and Chen, M. (2021): Automatic seismic phase analysis and earthquake location using Yinchuan array datasets based on a machine learning algorithm, *Earthquake*, **41**(1), 153–165, https://doi.org/10.12196/j.issn.1000-3274.2021.01.012.

Tian, X., Wang, M., Zhang, X., Wang, X., Sheng, S. and Lü, J. (2022): Discrimination of earthquake and quarry blast based on multi-input convolutional neural network, *Chinese J. Geophys.-Ch.*, **65**(5), 1802–1812 (in Chinese), 1802–1812.

Yang, S., Hu, J., Zhang, H. and Liu, G. (2021): Simultaneous earthquake detectionon multiple stations via a convolutional neural network, *Seismol. Res. Lett.*, **92**(1), 246–260, https://doi.org/10.1785/0220200137.

Yue, L., Qu, J., Zhou, S., Qu, B., Zhang, Y. and Xu, Q. (2023): Seismic event classification based on a two-step convolutional neural network, *J. Seismol.*, **27**(3), 527–535, https://doi.org/10.1007/s10950-023-10153-9.

Zhao, M., Tang, L., Chen, S., Su, J. and Zhang, M. (2021): Machine learning based automatic foreshock catalog building for the 2019 MS6.0 Changning, Sichuan earthquake, *Chinese J. Geophys.-Ch.*, **64**(1), 54–66 (in Chinese), https://doi.org/10.6038/cjg2021O0271.

Zhou, S., Jıang, H., Li, J., Qu, J., Zheng, C., Li, Y., Zhang, Z.. and Guo, Z. (2021): Research on identification of seismic events based on deep learning: Taking the records of Shandong seismic network as an example, *Seismology and Geology*, **43**(3), 663–676 (in Chinese), https://doi.org/10.3969/j.issn.0253-4967.2021.03.012.

Zhou, S., Jiang, H. K., Qu, J. H., Li, J., Guo, Z. B. and Zheng, X. (2021): A review on research progress in recognition of blasting, collapse, *Earthquake Research in China*, **37**(2), 508–522 (in Chinese)

Zhu, J., Song, J. and Li, S. (2022): Magnitude estimation of Yunnan Yangbi earthquake and Qinghai Madoi earthquake on May 21–22, 2021 based on deep convolutional neural network, *Chinese J. Geophys.-Ch.*, **65**(2), 594–603 (in Chinese), https://doi.org/10.6038/cjg2022P0584.

## SAŽETAK

## Istraživanje primjene tehnologije dubokog učenja za klasificiranje potresa i eksplozija pomoću lagane konvolucijske neuronske mreže

*Shaohui Zhou, Jian Li, Qijie Zhou, Yang Liu, Huilin Wang, Yu Wang, Chong Wang, Bing Lin, Han Zhang, Limei Peng i Dongya Li*

U ovom radu se predlaže lagani model konvolucijske neuronske mreže za brzo i točno prepoznavanje vrsta potresa i eksplozija. Budući da događaj u pravilu bilježi više postaja, potrebno je podatke prethodno obraditi i klasificirati prema događaju. Time se osigurava da se različiti valni oblici istog događaja ne pojavljuju u bilo koja dva skupa za obuku, skupa za provjeru valjanosti i skupa za testiranje. S trokomponentnim valnim oblicima koje su stanice zabilježile nakon predprocesiranja kao ulazom, mrežni model i hiperparametri optimizirani su analizom prosjeka i varijance u vrijednostima točnosti i gubitaka verifikacijskog skupa u peterostrukoj unakrsnoj provjeri te krivulja točnosti i gubitaka u procesu obuke. Na kraju, rezultati klasifikacije svih postaja koje postižu određeni omjer signala i šuma za svaki događaj uzimaju se kao izlaz ove vrste događaja na temelju načela da većina prevladava nad manjinom. Ova studija koristi 2.190 prirodnih događaja i događaja eksplozija koje je zabilježila Hainan Seismic Network prije kolovoza 2022., što uključuje 53.067 valnih oblika, za obuku i testiranje učinkovitosti modela. Dvadeset posto tih događaja odabrano je nasumično kao testni skup. Rezultati su pokazali da je od 438 nasumično odabranih događaja 427 točno identificirano, što je rezultiralo stopom točnosti od 97,48%. Točnije, stopa točnosti za seizmičke događaje bila je 95,59%, sa stopom prisjećanja od 89,04%, dok je stopa točnosti za događaje miniranja bila 97,84%, uz stopu prisjećanja od 99,18%. U zaključku, model konvolucijske neuronske mreže predložen u ovom radu može brzo i točno identificirati prirodne i eksplozivne vrste u Hainanu.

*Ključne riječi*: duboko učenje, klasifikacija, potres, miniranje, CNN-konvolucijska neuronska mreža

*Corresponding author's address*: Jian Li, Hainan Earthquake Agency, Meiyuan Road, Meilan District, Haikou City, Hainan Province, China; tel: +86 18 61 5689 283; e-mail: 694067345@qq.com