

Applied research of deep learning technology in the classification of earthquake and blasting event

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Abstract

In order to quickly and accurately identify the types of natural earthquake and non-natural earthquake events, this paper proposes a lightweight convolutional neural network model. Since generally an event can be recorded by several stations, data preprocessing and classification based on the event shall be carried out in advance in order to avoid the occurrence of different station waveforms of the same event in any 2 of the training set, validation set and test set. With the three component waveforms recorded by stations after preprocessing as the input, the network model and hypoparameters are optimized by analyzing the average and variance of the accuracy and loss values of the verification set in the five-fold cross-validation, as well as 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 minority is subordinate to the majority. In this study, 2190 natural earthquake and non-natural earthquake events recorded by the Hainan Seismic Network before August 2022 which contains 53067 waveforms are used to train and test the effect of the model. 20% of those events are selected randomly as the test set. The results showed that 427 of 438 randomly selected events were correctly identified, which means that the accuracy rate is 97.48%. Among them, the accuracy rate of seismic events was 95.59%, the recall rate was 89.04%, the accuracy rate of blasting events was 97.84%, and the recall rate was 99.18%. To sum up, the convolution neural network model constructed in this paper can quickly and accurately identify the types of natural and non-natural earthquakes in Hainan.

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 (Longfeng et al., 2017). At the same time, compared with natural earthquakes of the same magnitude, the source of non-natural events is shallow, and strong tremors are often felt; In addition, most of them occur in densely populated areas, which is characterized by high intensity (Qian Qihu, 2014; Zhou Shaohui, et al. 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 the 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 huge claims, and some people directly requested to deal with relevant personnel as man-made disasters.

Therefore, it is an extremely important work to quickly and accurately determine the event type after the seismic network has monitored various vibration events. In recent years, deep learning methods in the field of artificial intelligence have developed rapidly, and a large number of researchers have introduced them into the field of seismology, mainly including: automatic identification of seismic phases (Perol et al., 2018; Sujun et al., 2021; Guo Huili et al., 2022); Omission earthquake inspection and improvement of

earthquake catalogue (Yang et al., 2020; Zhao Ming et al., 2021; Zhu Jingbao et al., 2022); Earthquake prediction and prediction (Devries et al., 2018; Plaza et al., 2019; Asim et al., 2020), etc. At the same time, some researchers tried to introduce deep learning algorithm into the identification of vibration event types. For example, Linville et al(2019) used the time-frequency maps of blast and earthquake recorded waveforms as input, and used CNN and 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, and collapse events as input. Four structures of CNN were used for training respectively, the results showed that the recognition accuracy of all types of structures reached over 93% for both the training sets and test sets. Tian Qian et al(2022) used waveforms, spectra and polarity features of earthquake and blast events as input and used CNN for learning, eventually achieving recognition accuracy of up to 97%.

Each of the above researches has its own characteristics and has achieved good results. All of them adopt the current popular deep learning neural network that can automatically extract local abstract features. With various waveforms monitored by the station as input and relevant tags as output, they generate recognizers after training and learning a large amount of data, and finally achieve high accuracy recognition on the test set. However, due to the complexity of the recognition problem itself, the generalization ability of the classification model needs to be improved; If 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 Shaohui et al., 2021); The reason for this kind of problem may be that the waveform data in the unit of station is used as input during the training and testing of event waveform, 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 input of the classifier. This leads to the fact that the data selection in model training is not exactly the same as that in actual application, which leads 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.

Therefore, in order 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 selects all natural earthquake and non-natural earthquake event waveforms recorded by Hainan Seismic Network before August 2022 as the training set and test set, and randomly selects 438 events as the test set. In order to avoid the occurrence of waveforms which belong to the same event recorded by different stations in any two of the training set, verification set and test set (that is, a certain event can be recorded by several stations, but these waveforms must be in the same data set), the data preprocessing classification based on the event is conducted in advance, and then the convolutional neural network model is built. With the three channel waveforms recorded by the event stations after preprocessing as the input, the network model and super parameters are continuously optimized by analyzing the average and variance of the accuracy and loss values of the verification set in

the five fold cross validation, as well as the accuracy and loss curves in the training process. Finally, the event type discrimination 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 minority is subordinate to the majority. The convolutional neural network model is trained according to the real event type judgment in the actual earthquake quick report work, and its effect in the actual earthquake quick report work is tested, so as to provide technical support for the actual earthquake quick report work.

2. Method and principle

2.1 Data preprocessing

The classification of earthquake and blasting events is different from the traditional classification, in that the same event corresponds to multiple stations, and each station corresponds to three channel waveforms, which share the same classification label. In order to avoid the distortion of the accuracy rate of the model results caused by the occurrence of waveforms which belong to the same event recorded by different stations in any two of the training set, verification set and test set, the data preprocessing classification based on the event is carried out in advance in the preprocessing stage.

The data is divided into the training set, the verification set, and the test set by events, then the set consisting of training set and verification set is randomly divided into 5 parts. In order to ensure that the data input of the convolutional neural network are valid signals, the waveform of triggered seismic and blasting event stations is preprocessed as follows:

- (1) Waveform truncation: according to the arrival time of various seismic phases in the event waveform, take the station waveform as the unit to truncate the waveform signal with a length of 9000 points 30s before the arrival time of the seismic phase.
- (2) Detrend: perform the detrend operation on the truncated waveforms.
- (3) Filtering: High pass filtering is used to remove the long period components in the waveform.
- (4) Normalization: the waveform data is uniformly normalized and mapped to - 1 to 1.
- (5) Initial machine automatic filtering: calculate the signal-to-noise ratio of various waveforms, and set an appropriate threshold to filter waveforms.
- (6) Manual final confirmation: the waveforms of all stations after filtering shall be separately plotted in batches and checked manually to remove the waveforms of stations with abnormal waveforms.

2.2 Convolution neural network model

The convolution neural network model of waveform recognition is shown in Figure 1. The model can be divided into three parts: input layer, feature extraction layer and output layer. three-component seismic data with the length of 9000 sampling points after normalization processing are taken, and the

preprocessed seismic data enter the network structure from the input layer. The feature extraction layer mainly includes three convolution layers, three maximum pooling layers, one drop out layer and two full connection layers. All convolution layers in the feature extraction layer use the relu activation function. The first full connection layer uses the relu activation function, and the second full connection layer uses the softmax activation function. To avoid over fitting, this model adds a drop-out layer that can randomly "discard" some nodes, thus improving the generalization ability of the model. Finally, the convolutional neural network model generates 18562 training parameters. The output layer is a sequence with a length of 2. After the input layer and the feature extraction layer, the vector with a length of 2 is output at the output layer. When the first bit is 1, it means blasting, and when the second bit is 1, it means earthquake.

2.3 Model training and parameter adjustment

The convolution neural network model is trained according to the real event type judgment in the actual earthquake quick report work. The waveform after data preprocessing is divided into the training set, the verification set, and the test set by the unit of events. The set composed of training set and verification set is trained in the way of five-fold cross validation, that is, the set composed of training set and verification set is randomly divided into five sets, with a total of five times of training. One of them is taken as the verification set in turn, and the remaining four are taken as the training set. Take the average training result of five times as the accuracy and loss value of this training, and optimize the network structure and hyperparameter according to this value and the loss and accuracy curve of the training process. When the hyperparameter are adjusted to the optimum, the test set is fed to the network to objectively evaluate the performance of the network.

Figure 2 shows the main data processing framework of this study, but the preprocessing process is omitted due to space constraints. Including: training set processing flow, verification set processing flow, and test set processing flow. These three parts have the same input method: label the waveforms corresponding to each event, disrupt the order of all waveforms with corresponding labels, input 128 waveforms as a group into the network, forward propagate to generate prediction labels, use prediction labels and real labels to calculate the cross entropy loss value, and accuracy.

The unique feature in the training set processing process is that it will back propagate, update the network parameters, and call all waveforms input into the network an epoch of training. After each epoch of training, the verification set waveforms will be input into the network in the same way. Similarly, after all the verification sets are input into the network, the cross entropy, loss value and accuracy rate can be calculated based on the prediction label and the corresponding input waveform label. The difference between the test set and the verification set is that the model selected in the test set is the final trained model. The label predicted by the model also needs to be a new organization set based on the event. In each event, the prediction results of each station waveform are integrated to give a final prediction value. Finally, the prediction value of each event and the real value label of each event in the test set are used to calculate the accuracy, precision, recall and F1 score based on the event. Among them, the ground truth

label is converted into a unique hot coding, and the prediction label is a 2-bit array produced through the softmax layer.

In each epoch of training, data will be randomly truncated into a waveform with a length of 9000 points. The data has a 30% probability of data enhancement. The data enhancement includes random translation of the designated area of the data and increasing the Gaussian noise with a fixed signal to noise ratio, which can 'create' more seismic data, reduce the occurrence of over fitting, and improve the generalization ability of the model.

3. Data

In this paper, all natural and non-natural earthquake events recorded by Hainan Seismic Network Center before August 2022 are used as training samples and test samples. 438 events are randomly selected as test set according to the proportion of natural and non-natural earthquakes in the data set, and the rest are training set and validation set. In the training set, a five-fold cross validation method is adopted for evaluation.

There are 24 observation stations for these events. Waveforms recorded by each station include vertical, east-west and north-south directions. There are 1752 events, 292 earthquake events and 1460 non-natural earthquake events in the training set. For each event, the matrix composed of three component data of each station is taken as the training sample. There are 14155 training samples, including 4068 seismic samples and 10087 non-natural seismic samples. There are 438 events, 73 earthquake events and 292 non-natural earthquake events in the test set. There are 3534 test samples, including 976 earthquake samples and 2558 non-natural earthquake samples.

4. Training results and model evaluation

In order to test the discrimination efficiency of the deep learning convolution neural network proposed in this paper in the real-time operation process of digital seismic network, 3534 station waveforms of 438 events were randomly selected as the test set for evaluation, and the model identification effect was evaluated respectively in waveform unit and event unit; Specifically, confusion matrix, accuracy rate, recall rate and F1 score are used to evaluate the accuracy of the model.

Among 3534 waveforms in the test set, there are 976 natural earthquake waveforms and 2558 blasting waveforms. Table 1 shows the confusion matrix of earthquake and blasting identification results in the unit of waveform, in which the sum of the number of each line represents the number of real events of this category. Table 2 shows the accuracy rate, recall rate and F1 score of the model recognition in the unit of waveform. According to Table 1 and Table 2, 819 seismic waveforms and 2552 blasting waveforms in the test set are identified correctly; 36 blasting waveforms are identified as earthquakes, and 157 seismic waveforms are identified as explosions; The accuracy rate of blasting waveform is 94.14%, and the recall rate is 98.59%; The accuracy rate of seismic waveform is 95.79%, and the recall

rate is 83.91%; The overall comprehensive recognition accuracy is 94.54% (Table 2). It shows that the convolution neural network model constructed in this paper can quickly and accurately determine the type of natural earthquake and blasting of the waveform of a single station.

Table 1 Confusion Matrix of Earthquake and Blasting Identification Results of the Model in Waveform

	blasting[predicted]	earthquake (predicted)
blasting[true]	2522	36
earthquake[true]	157	819

Table 2 precision, recall rate, 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 actual event type determination work, the final determination is based on the type of each station rather than the waveform of a single station. Therefore, the model built in this paper is evaluated for the effect of event based type identification; In the event based assessment, the waveforms of all corresponding stations meeting a certain signal-to-noise ratio of the event are identified respectively, and the principle of the minority obeying the majority is finally adopted as the judgment result of the event type. There were 73 natural earthquakes and 365 blasting events in 438 events. Table 3 shows the confusion matrix of the identification results of natural earthquake and blasting in the test set based on events, and Table 4 shows the identification accuracy, recall and F1 score of the model in the test set based on events. The results show that 362 of 365 blasting events are correctly identified, and 65 of 73 natural earthquakes are correctly identified; Eight natural earthquakes are identified as blast, and three blasting events are identified as earthquakes; The accuracy rate of blasting events is 97.84%, and the recall rate is 99.18%; The accuracy rate of natural earthquake is 95.59%, and the recall rate is 89.04%; The overall comprehensive recognition accuracy is 97.49%. It shows that the convolution neural network model constructed in this paper can quickly and accurately identify the types of natural earthquake and blasting events.

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, 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

5. Discussion and Conclusion

(1) In order to quickly and accurately identify non-natural earthquakes and natural earthquakes in Hainan, different from most conventional convolutional neural network input images, this paper built a convolutional neural network model according to the characteristics of seismic signals, which reduces the network volume and data space, thus reducing the space occupied by massive data. At the same time, in order to optimize the training process, Data dynamic reading preprocessing and loading are adopted, and the training process loads data as required, so that the data input in each round of training is different from the previous one. Theoretically, training is no longer limited by the size of computer memory, and there is no limit on the amount of data, which is applicable to the training of massive data models. When loading data, data enhancement processing is carried out on the data, so that more different data can be produced with limited data.

(2) All natural and non-natural earthquake events recorded by Hainan Seismic Network before August 2022 are selected as dataset. Based on the signal characteristics of the same event corresponding to multiple observation stations, each station corresponds to a 3-channel waveform. In order to avoid the occurrence of different station waveforms of the same event in any 2 of the training set, verification set and test set, data preprocessing and classification are conducted in advance based on the event, With the three component signals recorded by the event stations after preprocessing as the input, the network model and hypoparameters are continuously optimized by analyzing the average and variance of the accuracy and loss values of the verification set in the five fold cross validation, as well as the accuracy and loss curves in the training process. Finally, the event type discrimination 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 minority is subordinate to the majority.

(3) In the process of network training, we should pay attention to the following problems, so we must check the data. If a null value appears in the entire data set, the network accuracy and loss value will not change with the training process, and error troubleshooting will also take time. The data input in the actual network prediction must be completely consistent with the training set, The experiment shows that if the training set uses the regularization method to process the data and the verification set uses the normalization method to process the data, the result will be very poor.

(4) 3534 waveforms of 438 events in total are randomly selected as the test set for evaluation, and the model recognition effect is evaluated by taking waveform as the unit and event as the unit respectively. The results show that the accuracy rate of blasting waveform is 94.14%, the recall rate is 98.59%, and F1 score is 0.9631 in the model effect evaluation with station waveform as the unit; The accuracy rate of seismic waveform is 95.79%, the recall rate is 83.91%, and F1 score is 0.8946; The overall comprehensive recognition accuracy is 94.54%; In the model effect evaluation with events as the unit of test set, the accuracy rate of blasting events is 97.84%, the recall rate is 99.18%, and F1 score is 0.9850; The accuracy rate of natural earthquake is 95.59%, the recall rate is 89.04%, and F1 score is 0.9220; The overall comprehensive recognition accuracy is 97.49%. It shows that the convolution neural network model constructed in this paper can quickly and accurately identify the types of natural earthquake and blasting events, regardless of the waveform of a single station or a single event.

In conclusion, the classification model based on convolutional neural network proposed in this paper has a good effect on Hainan dataset. In order to achieve the optimal effect, the next step can try to improve the recognition accuracy of the model by increasing the amount of training data, designing a more intelligent waveform filtering program, and increasing the available training waveforms on the basis of ensuring the accuracy of the training set label. Waveforms of Multi events stacking are more likely classified as earthquakes. Since the situation rarely happens, and the number of training waveforms are hard to increase, reducing the false recognition rate in this case relies on other systems like the correlation algorithm of seismic phase pickup which can indicate the muti waveform stacking in advace.

Declarations

Data Availability

The waveform recording of earthquake and blasting data used to support the findings of this study were supplied by Earthquake Agency of Hainan Seismological Bureau under license and so cannot be made freely available. Requests for access to these data should be made to Zhou Shaohui, 674891062@qq.com.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

1. Asim K M,MoustafaSS,NiazIA,etal.Seismicity analysis and machine learning models for Shortterm low magnitude seismic activity predictions in Cyprus[J].soil dynamics and earthquake engineering,2020,130:105932.
2. Devries P M R, Viégas F, Wattenberg M, et al. 2018.Deep learning of aftershock patterns following large earthquakes[J].nature.
3. Grigoli F, Cesca S, Rinaldi A P, et al. The November 2017 *M*_w 5.5 Pohang earthquake: A possible case of induced seismicity in South Korea[J]. Science, 2018,360: 1003–1006.DOI: 10.1126/science.aat2010.
4. GUO HuiLi, CHANG LiJun, LU LaiYu, WU PingPing, LÜ MiaoMiao, DING ZhiFeng. 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 Journal of Geophysics (in Chinese), 65(5): 1628–1643, doi: 10.6038/cjg2022P0863
5. Huang R, Zhu L, Encarnacion J, et al. Seismic and geologic evidence of water-induced earthquakes in the Three Gorges Reservoir region of China[J]. Geophysical Research Letters, 2018, 45: 5929–5936. DOI:10.1029/2018GL077639
6. Kim K H, Ree J H, Kim Y, et al. Assessing whether the 2017 *M*_w 5.4 Pohang earthquake in South Korea was an induced event.[J]. Science, 2018, 360:1007–1009.DOI: 10.1126/science.aat6081.
7. Linville L,Pankow K,Draeos T.2019.Deep learning models augment Analyst decisions for event discrimination.Geophysical Research Letters,46(7):3643–3651.
8. Long Feng,Luan Xiang.2017Challenges and research prospects of induced earthquakes[J]. Recent Developments in World Seismology, 47(5):11–15.
9. Perol T, Gharbi M, Denolle M. 2018. Convolutional neural network for earthquake detection and location[J]. Science Advances,4(2): e1700578.
10. Plaza F,Salas R,Nicolis O.Assessing seismic hazard in chile using deep neural networks[M]||Natural Hazards Risk, Exposure, Response, and Resilience. IntechOpen, 2019.
11. Qian Qihu.Definition, mechanism, classification and quantitative forecast model for rockburst and pressure bump[J].Rock and Soil Mechanics,2014,35(1):1–6.
12. Su Jun,Wang Weilai,Zhang long,et al..Automatic Seismic Phase Analysis and EarthquakeLocation Using Yinchuan Array Datasets based on a Machine Learning Algorithm[J].EARTHQUAKE.41(1): 153–165.
13. Tian Xiao,Wang Mingju,Zhang Xiong,et al..Discrimination of earthquake and quarry blast based onmulti-input convolutional neural network.Chinese Journal of Geophysics,65(5):1802–1812
14. Yang S B,Hu J, Zhang H J,et al.2020. Simultaneous earthquake detectionon multiple stations via a convolutional neural network. Seismological Research Letters,2020, doi:10.1785/0220200137
15. Zhao Ming,Tang Lin,Chen Shi etc.Machine learning based automatic foreshock catalog building for the 2019 MS6.0 Changning,Sichuan earthquake.Chinese Journal of Geophysics,64(1):54–66.

16. ZHOU Shao hui, JIANG Hai kun,LIJian,etal.2021.Research on identification of seismic events based on deep learning:Taking the Records of Shandong seismic network as an example[J]. Seismology and eology,43(3):663–676.
17. ZHOU Shao hui, JIANG Hai kun,QU Junhao,etal.2021.A Review on Research Progress in Recognition of Blasting, Collapse[J].Earthquake Research in China(in Chinese),,37(2): 508–522.
18. ZHU JingBao, SONG JinDong, LI ShanYou. 2022. Magnitude estimation of Yunnan Yangbi earthquake and Qinghai Madoi earthquake on May 21–22, 2021 based on deep convolutional neural network. Chinese Journal of Geophysics (in Chinese), 65(2): 594–603, doi: 10.6038/cjg2022P0584

Figures

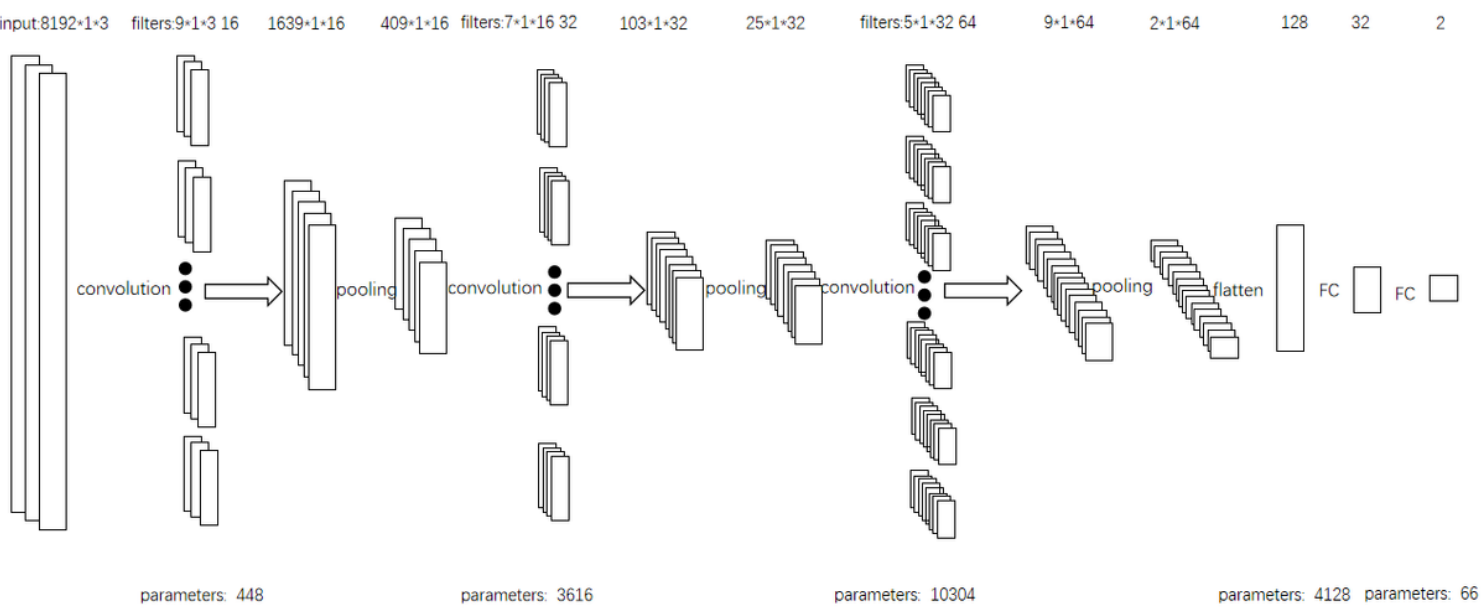


Figure 1

Convolution neural network model

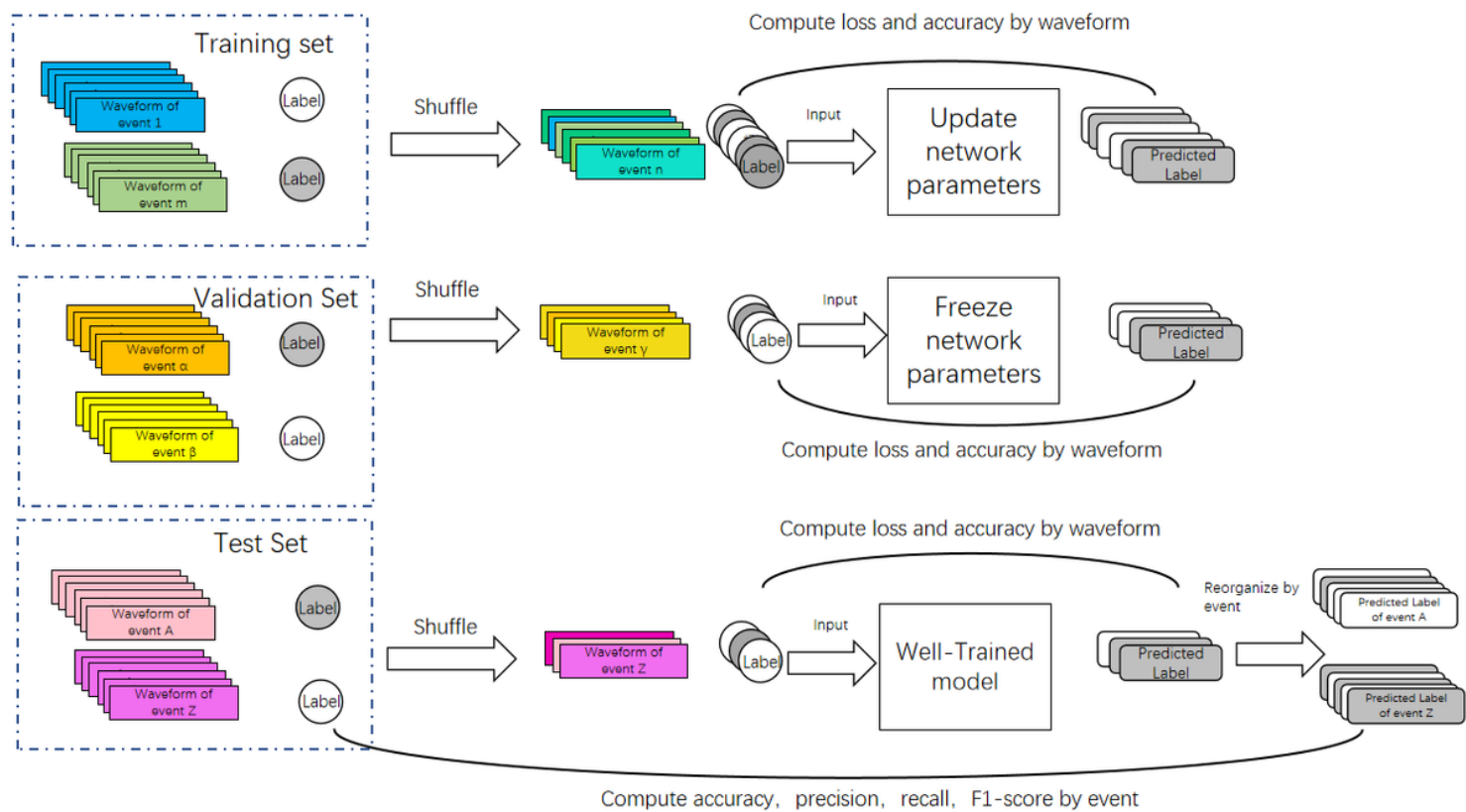


Figure 2

Flow chart of algorithm data in this paper