Deep Learning-based Small Magnitude Earthquake Detection and Seismic Phase Classification

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\textbf{ABSTRACT}

Reliable earthquake detection and seismic phase classification is often challenging especially in the circumstances of low magnitude events or poor signal-to-noise ratio. With improved seismometers and better global coverage, a sharp increase in the volume of recorded seismic data is witnessed. This makes the handling of the seismic data rather daunting based on traditional approaches and therefore fuels the need for a more robust and reliable method. In this study, we investigate two deep learning-based models, termed 1D Residual Neural Network (ResNet) and multi-branch ResNet, for tackling the problem of seismic signal detection and phase identification, especially the later can be used in the case where multiple classes is organized in the hierarchical format. These methods are trained and tested on the dataset of the Southern California Seismic Network. Results demonstrate that the proposed methods can achieve robust performance for the detection of seismic signals, and the identification of seismic phases, even when the seismic events are of small magnitude and are masked by noise. Compared with previously proposed deep learning methods, the introduced frameworks achieve 4% improvement in earthquake monitoring, and a slight enhancement in seismic phase classification.

\textbf{1. Introduction}

The detection of earthquake events is crucial for seismologists to optimally monitor tectonic activities in a region. In order to achieve reliable earthquake monitoring, many automated methods for seismic phase picking have been developed. The most state-of-the-art conventional algorithms for earthquake detection or picking seismic phase include template matching Peng and Zhao (2009); Ross, Rollins, Cochran, Hauksson, Avouac and Ben-Zion (2017), short-time average/long-time average (STA/LTA) Allen (1978), and autoregressive Akaike Information Criterion-picker (AR-AIC) Sleeman and Van Eck (1999). Template matching involves measuring the similarity between earthquake waveforms and catalogued waveforms of seismic events. STA/LTA refers to measuring the ratio between the amplitude of the signal on a short time window with that on a long time window, and the detection can be determined when the ratio is greater than some pre-defined threshold. AR-AIC involves two main calculations: AR and and AIC, where the minimum of the two-model AIC is identified as the phase arrival time, and this method is mainly based on the assumption that the seismogram can be divided into different locally stationary segments St-Onge (2011). However, template matching relies heavily on the pre-defined events, this makes the detection challenging in case of unfamiliar data Ross, Meier, Hauksson and Heaton (2018). On the other hand, both STA/LTA and AIC do not perform well for the signals with low signal-to-ratio (SNR) signal especially in the case of low magnitude events. In addition, given seismic recordings associated with low SNRs, AR-AIC is potential to produce several local minimal AIC value that results in false arrival time picking Dong, Jiang, Li and Yang (2019).

Over the past decades, due to the development of seismic equipment and seismic monitoring network, remarkable improvements have been achieved in seismic event detection system which brings about huge and rapidly-increasing seismic database. This thus calls for robust and sensitive methods to address the ever growing volume of seismic data. Therefore, seismic event detection and phase picking algorithms are becoming increasingly important to automatically deal with large seismic data. Deep learning, with its recent development - especially in computer vision, is capable to process big data and with a large number of different features such as lines, edges, image segments. The task of earthquake signal detection or seismic phase identification can be recognized as similar to the identification of objects in computer vision. Therefore, the recent advances in the field of computer vision have great potential in seismological applications. Recently, deep learning has been widely used to detect earthquakes or identify seismic phases Ross et al. (2018); Saad and Chen (2020, 2021); Chakraborty, Li, Faber, Ruempker, Stocker and Srivastava (2021). For example, in Ross et al. (2018), a convolutional neural network was...
trained on the huge amount of labeled seismic data to classify seismic body wave phase.

In this work, both the earthquake detection and seismic phase identification are formulated as a supervised classification problem. Considering that ResNet He, Zhang, Ren and Sun (2016) achieves superiority in image classification by adopting skip connection and 1D ResNet works well for time-series data (e.g., valve acoustic signals) Sha, Faber, Gou, Liu, Li, Schramm, Stoecker, Steckensreiter, Vnuvec, Wetzstein et al. (2022), in this study we investigate two deep learning-based methods: 1D ResNet34 based on the residual module He et al. (2016) and 1D multi-branch ResNet for the defined task (more details in section 2). The seismic data of the Southern California Seismic Network Center (2013) labeled as 'P-phase', 'S-phase' and 'Noise' (more details in section 3.1) is employed to train the model and test it's performance. The model performance well indicates that the proposed methods for earthquake detection are not only capable of robustly classifying seismic signals and noise data, but also allows to reliably identify P-waves and S-waves of small magnitude earthquakes.

This work is organized as follows. Section 2 comprehensively delineates the proposed methodologies. Section 3 briefly describes the used dataset, and shows the experiment setting and metrics for performance evaluation. Section 4 details the results of the performed experiments. Finally, Section 5 describes the conclusions of this work.

2. Methodology

The proposed methods described in this section are taking a window of three-channel waveform seismogram data (e.g., three-channel normalized waveform within the duration of 4s) as input. Note that in this work the two tasks (earthquake detection and Phase classification) are separately implemented when using 1D ResNet, while they are completed simultaneously in the case of multi-branch ResNet with reduced number of model parameters. Therefore, in the task of earthquake detection, the output is labeled as earthquake (including but not distinguishing P wave and S wave) and noise signals same as Saad and Chen (2020), while in the case of seismic phase classification, the model is trained to classify noise, P wave, and S wave, respectively, similar to Ross et al. (2018); Saad and Chen (2021).

For those two tasks, in the model training process, the labels are defined as follows: (i) for earthquake detection - 'zero' for earthquake signal and 'one' for noise. (ii) for phase classification - 'zero' for P-wave windows, 'one' for S-wave windows, and 'two' for noise windows.

Considering the complexity during training and memory consumption, in the multi-branch architecture, two branches are used with one coarse branch for earthquake and noise identification, and one fine branch for seismic phase classification (P-phase, S-phase, Noise).

2.1. Residual neural network

He et al. (2016) revealed that when adding more layers to the neural network to enrich the features of the model, training the neural network becomes more challenging due to difficulty in optimizing the model parameters caused by vanishing/exploding gradient. Furthermore, the accuracy of the model either gets saturated at a particular value, or slowly degrade. Consequently, the model performance deteriorates both in the training phase and testing phase. To tackle this issue, He et al. He et al. (2016) proposed the popular neural network architecture known as ResNet, where the layers are explicitly reformulated as learning residual functions with respect to the layer input. The idea is that it is easier to optimize the residual function \( F(x) \) than the original function \( H(x) = F(x) + x \). They also provided extensive empirical evidence to indicate that it is not only easier to optimize these residual networks, but also the accuracy could be enhanced from the considerably increased depth. The Residual block is denoted in Figure 1.

The skip connections in ResNet succeeded in dealing with the issue of vanishing gradient in deep neural networks by allowing the gradient to flow directly through the alternative shortcut path backward from latter layers to former layers. On the other hand, these connections allow the model to learn the identity functions, which guarantees that the higher layer could perform at least as good as the lower layer, and not worse.

In this study, 1D ResNet is developed for earthquake detection and seismic phase classification. The only difference between these two tasks is the output size. In our work, the seismic records with three-components are identified as images by the devised 1D ResNet to detect earthquake signals from noisy data and further to identify seismic phases to P-wave or S-wave, correspondingly.

2.2. Multi-branch Residual Neural Network

A 1D multi-branch ResNet based architecture is developed to perform earthquake detection and seismic phase classification simultaneously. This model combines several
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Figure 2: Architecture of Multi-Branch ResNet. The network at the bottom can be an arbitrary ResNet. There can be multiple branch networks and each of them outputs a prediction. The final loss function is a weighted sum over all branch losses.

![Diagram of Multi-Branch ResNet](image)

Figure 3: A sample hierarchical label tree where classes are taken from SCEDC dataset.

In this study, the loss function of the developed 1D multi-branch ResNet can be achieved by summing all branch losses assigned with different weights. Hence, the loss function can defined as follows:

$$
\mathcal{L}_{\text{total}} = w_1 \ast \text{loss}_1 + w_2 \ast \text{loss}_2
$$

where $w_1$ and $w_2$ are the weights for the noise/earthquake detection, and seismic phase classification, respectively. And $\text{loss}_1$ and $\text{loss}_2$ denote the losses of two branches. In this paper, we set $w_{\text{branch}} = 0.5$ for simplicity.

3. Analysis

3.1. Seismic Dataset

Within this study, the dataset provided by Southern California Earthquake Data Center (SCEC) Center (2013) is utilized to train and test the proposed model. The magnitude range of the data is $-0.81 < M < 5.7$. The dataset includes 1.5 million P-wave seismograms, 1.5 million S-wave seismograms, and 1.5 million noise windows with each record of 4s duration. Both P-wave and S-wave windows are centered on the arrival time, while each noise window is captured by starting 5s before each P-wave arrival pick. Figure 4 visualizes the waveforms including P-phase window, S-phase window and noise window.

In order to help better understand the model output, here Figure 5 shows the pipeline of the testing process, and gives a visualization of the testing result (the predicted probability) using the pie chart of three different input data extracted from one raw waveform of STEAD dataset Mousavi, Sheng, Zhu and Beroza (2019) when fed in the pre-trained model. Similar to SCEDC dataset Center (2013), the P-phase and S-phase windows are centered on the respectively arrival time, and the noise windows are extracted starting 5s before the P arrival time. Each pie chart, shows the predicted probability for each class (P-phase, S-phase, Noise), in which the sum over all the probability is one.
Figure 4: Waveform visualization of SCEDC data Center (2013). These waveforms are resampled at 100 Hz and normalized using the absolute maximum amplitude over three components.

Figure 5: Output visualization of one testing example from STEAD dataset Mousavi et al. (2019), where the pie chart displays the predicted probability for the classes corresponding to different input data.
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Table 1
Testing accuracy for two tasks.

| Model                                      | Earthquake detection | Phase classification |
|--------------------------------------------|----------------------|----------------------|
| CapsNet Saad and Chen (2020) (50% training)| 98.40%               | -                    |
| CapsPhase Saad and Chen (2021) (90% training)| -                   | 98.67%               |
| 1D ResNet                                  | 98.83%               | 98.70%               |
| Multi-branch ResNet (50% training)         | 98.85%               | 98.41%               |
| Multi-branch ResNet (90% training)         | 98.96%               | 98.66%               |

3.2. Experiment Setting

In this study, the learning rate of 0.001 is used and the model is trained till 50 epochs same as CapsPhase Saad and Chen (2021) to achieve an unbiased comparison. The proposed models are implemented in PyTorch Paszke, Gross, Massa, Lerer, Bradbury, Chanan, Killeen, Lin, Gimelshein, Antiga et al. (2019) and trained on an NVIDIA A100 Graphics Processing Unit. The ADAM Kingma and Ba (2014) algorithm is adapted to optimize our models by using a cross-entropy loss function in the mini-batches of 480 records. A dropout rate of 0.2 is adopted for all dropout layers. Note that here, the data augmentation is not used on the training data and at the same time, we do not utilize any ensemble methods in the model training phase.

Aiming to make the comparison with CapsNet Saad and Chen (2020) for the earthquake detection task, 50% of the whole dataset is used for model training and 25% of the data is utilized for testing. However, in CapsNet Saad and Chen (2020), the training dataset is balanced, i.e., the number of the data labeled by zero (‘earthquake’) is same as the number of the data with labels of one (‘noise’). Please note the fact that, from the beginning on, the whole dataset is labelled with one of the three classes: P-phase, S-phase or noise. In our study, the first 50% of the whole data is used for training. On other hand, in the case of earthquake and non-earthquake detection, the wave windows including P-phase and S-phase are re-labeled as earthquake signals. The abovementioned processes make the training dataset biased, where the number of the data labeled by zero (earthquake) is not equal to that labeled by one (noise). Owing to this, it is more difficult to train the model in our work. This can further test the model performance like robustness on imbalanced data which is common in real-world applications of deep learning. Furthermore, for seismic phase identification, we split the seismograms into a training set (90%) and testing set (5%) same as CapsPhase Saad and Chen (2021). Nevertheless, it is worth noting that only in the task for earthquake identification, the training dataset is imbalanced, while in the seismic phase classification, the training dataset is unbiased.

3.3. Evaluation Metric

The following metrics are utilized to evaluate the model performance. First, the accuracy is defined as the ratio of correctly identified instances over all testing samples, which is usually regarded as the basic measurement of a classifier’s performance.

\[
\text{Accuracy} = \frac{N_C}{N_T}
\]

where \(N_C\) denotes the number of correctly labeled samples and \(N_T\) represents the number of all testing samples.

Then, in order to further estimate the model’s effectiveness, the confusion matrix Stehman (1997) is employed to reflect the classification result. Furthermore, given a confusion matrix, the precision, recall and F1-score can be defined as follows:

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

\[
\text{Recall} = \frac{TP}{TP + FN}
\]

\[
F_1\text{-scores} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

where TN, FN, FP, and TP are the true negative, false negative, false positive, and true positive, respectively.

4. Discussions

The overall testing accuracy for earthquake detection and phase classification of different methods is compared and summarized in Table 1. We can find that the testing accuracy of 1D ResNet and multi-branch ResNet is 98.83% and 98.85%, respectively. The result demonstrates that our proposed model achieves better performance for earthquake detection over CapsNet Saad and Chen (2020). For seismic phase classification, 1D ResNet demonstrates its superiority, and multi-branch ResNet also achieves a compatible performance compared with CapsPhase Saad and Chen (2021). The potential reasons to achieve higher performance are twofold. First, the residual blocks in ResNet He et al. (2016) contribute to improve the classification accuracy, since it is capable to learn some meaningful features from the input. Second, the hierarchical structure in multi-branch ResNet as prior knowledge could have enhanced model performance.

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Table 2
Testing results for earthquake detection on the testing data.

| Category  | Model                              | Precision | Recall  | F1-score |
|-----------|------------------------------------|-----------|---------|----------|
| Earthquake| CapsNet Saad and Chen (2020)       | 98.64%    | 98.98%  | 98.80%   |
|           | ResNet                             | 99.18%    | 98.06%  | 99.12%   |
|           | Multi-branch ResNet (50% training) | 97.77%    | 98.82%  | 98.29%   |
| Noise     | CapsNet Saad and Chen (2020)       | 97.96%    | 97.30%  | 98.70%   |
|           | ResNet                             | 98.13%    | 98.37%  | 98.25%   |
|           | Multi-branch ResNet (50% training) | 99.40%    | 98.87%  | 99.14%   |

Table 3
Testing results for phase classification on the testing data.

| Category | Model                              | Precision | Recall  | F1-score |
|----------|------------------------------------|-----------|---------|----------|
| P phase  | CapsPhase Saad and Chen (2021)     | 98.68%    | 98.99%  | 98.76%   |
|          | ResNet                             | 98.88%    | 98.64%  | 98.76%   |
|          | Multi-branch ResNet (90% training) | 98.84%    | 98.58%  | 98.71%   |
| S Phase  | CapsPhase Saad and Chen (2021)     | 98.40%    | 98.88%  | 98.70%   |
|          | ResNet                             | 98.72%    | 98.94%  | 98.83%   |
|          | Multi-branch ResNet (90% training) | 98.88%    | 98.68%  | 98.78%   |
| Noise    | CapsPhase Saad and Chen (2021)     | 98.90%    | 98.17%  | 98.53%   |
|          | ResNet                             | 98.52%    | 98.54%  | 98.53%   |
|          | Multi-branch ResNet (90% training) | 98.26%    | 98.73%  | 98.49%   |

Figure 6: Visualization of mis-classified SCEDC data. These waveforms are resampled at 100Hz and normalized using the absolute maximum amplitude over three components.
The results of different metrics including precision, recall and F1-score for earthquake identification are shown in Table 2. It is found that 1D ResNet and multi-branch ResNet can achieve compatible results. Particularly, for noise detection, the proposed multi-branch ResNet reaches a best performance.

Finally, Table 3 summarizes the classification result of different metric for seismic phase identification. It can be observed that compared with CapsPhase Saad and Chen (2021), the proposed models achieve a better performance, especially for P wave and S wave identification.

Figure 6 visualizes an example for each class including P-phase window, S-phase window and noise window from SCEDC dataset that are mis-classified using the proposed 1D-ResNet in this work.

5. Conclusions
In this study, we investigate two deep learning-based models for simultaneous earthquake detection and seismic phase classification. The methods are based on a well-designed architecture using a 1D residual neural network (ResNet). These models are trained and tested on the Southern California Seismic Dataset. Extensive experiment results verify that both the used method and the proposed multi-branch ResNet achieve better performance than previous deep learning based approaches. The proposed model can be utilized by seismologist to identify the earthquake signals and phase identification, especially in the case of noisy low magnitude earthquake waveforms. The future work will focus on a straightforward hierarchical classifier to reduce the training complexity and memory.

6. Code and Data Availability
The code is available on GitHub at https://github.com/srivastavaresearcghgroup/Seismic-phase-Classification. The Southern California seismic data that support this study can be accessed in Center (2013).

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Wei Li: Conceptualization, Methodology, Software, Writing - Original Draft, Writing - Review and Editing. Yu Sha: Methodology, Kai Zhou: Methodology, Writing - Review and Editing. Johannes Faber: Methodology, Writing - Review and Editing. Georg Rümpker: Conceptualization, Writing - Review and Editing. Horst Stöcker: Writing - Review and Editing. Nishtha Srivastava: Conceptualization, Methodology, Writing - Review and Editing.

References
Allen, R.V., 1978. Automatic earthquake recognition and timing from single traces. Bulletin of the seismological society of America 68, 1521–1532.
Center, S.C.E.D., 2013. Southern california earthquake data center (2013). California Institute of Technology, Dataset Doi:10.7909/C3WD3xH1.
Chakraborty, M., Li, W., Faber, J., Ruempker, G., Stoecker, H., Srivastava, N., 2021. A study on the effect of input data length on deep learning based magnitude classifier. arXiv preprint arXiv:2112.07551.
Dong, X., Jiang, H., Li, Y., Yang, B., 2019. Arrival time picking of microseismic data by using deep learning. JOURNAL OF SEISMIC EXPLORATION 28, 475–494.
He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770–778.
Kingma, D.P., Ba, J., 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
Mousavi, S.M., Sheng, Y., Zhu, W., Beroza, G.C., 2019. Stanford earthquake dataset (stead): A global data set of seismic signals for ai. IEEE Access 7, 179464–179476.
Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., et al., 2019. Pytorch: An imperative style, high-performance deep learning library. arXiv preprint arXiv:1912.01703.
Peng, Z., Zhao, P., 2009. Migration of early aftershocks following the 2004 parkfield earthquake. Nature Geoscience 2, 877–881.
Ross, Z.E., Meier, M.A., Hauksson, E., Heaton, T.H., 2018. Generalized seismic phase detection with deep learning. Bulletin of the Seismological Society of America 108, 2894–2901.
Ross, Z.E., Rollins, C., Cochran, E.S., Hauksson, E., Avoauc, J.P., Ben-Zion, Y., 2017. Aftershocks driven by afterslip and fluid pressure sweeping through a fault-fracture mesh. Geophysical Research Letters 44, 8260–8267.
Saad, O.M., Chen, Y., 2020. Earthquake detection and p-wave arrival time picking using capsule neural network. IEEE Transactions on Geoscience and Remote Sensing.
Saad, O.M., Chen, Y., 2021. Capsphase: Capsule neural network for seismic phase classification and picking. IEEE Transactions on Geoscience and Remote Sensing.
Sha, Y., Faber, J., Gou, S., Liu, B., Li, W., Schramm, S., Stoecker, H., Steckenreiter, T., Vnuccce, D., Wetzstein, N., et al., 2022. A multi-task learning for cavititation detection and cavititation intensity recognition of valve acoustic signals. arXiv preprint arXiv:2203.01118.
Sleeman, R., Van Eck, T., 1999. Robust automatic p-phase picking: an on-line implementation in the analysis of broadband seismogram recordings. Physics of the earth and planetary interiors 113, 265–275.
St-Onge, A., 2011. Akaike information criterion applied to detecting first arrival times on microseismic data, in: SEG Technical Program Expanded Abstracts 2011. Society of Exploration Geophysicists, pp. 1658–1662.
Stehman, S.V., 1997. Selecting and interpreting measures of thematic classification accuracy. Remote sensing of Environment 62, 77–89.