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Study on the use of CNN models for high-pass filter frequency in ground motion data generation for evaluating seismic fragilities

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1. Introduction

The Korean Peninsula, located on the southeastern part of the Eurasian plate, belongs to the intraplate region. The characteristics of intraplate earthquakes show the low and rare seismicity and the sparse and irregular distribution of epicenters compared to interplate earthquakes. So, it has traditionally been considered a seismically safe region. However, the 9.12 Gyeongju earthquake (Sep. 12, 2016, ML 5.8) and the Pohang earthquake (Nov. 15, 2017, ML 5.4) have occurred, led to the need to re-evaluate the seismic vulnerability of buildings, bridges, and dams.

Many ground motion data and proper processing are essential for accurate seismic vulnerability assessments. PEER (The Pacific Earthquake Engineering Research Center), known for NGA (Next Generation Attenuation) database [1], has been processing many ground motion data for the NGA project. The processing method is: 1) remove instrument response from seismic waveform; 2) remove offset by cosine taper and demean; 3) convert to acceleration data; 4) To determine high pass filtering frequency, compare FAS (Fourier amplitude spectrum) between noise and seismic windows or review the filtered displacement graph; 5) apply the causal Butterworth filter. However, determining high-pass frequency by visual inspection is subject to human error and is inefficient for large amounts of data. To solve this problem, we adopted a deep learning model.

Humans are more sensitive to differences between lower frequencies than higher frequencies. Mel-Spectrogram takes it into account by using the Mel Scale instead of frequency. In seismology, Mel-Spectrograms are used to identify noise [2] and detect earthquakes [3]. And we also deal with earthquakes and noise problem. So, we pre-processed the time series and extracted features by mel-spectrogram.

In this study, we employed CNN (Convolution Neural Network) models. It is feasible to automatically extract the high dimensional feature from the data and has already been successfully applied to image classification, speech recognition and various other domains. Additionally, we adopted transfer learning. Transfer learning effectively reduces the model convergence time and the data demand. R^2, RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error) were adopted to evaluate the accuracy and loss.

2. Methods and Results

2.1 Dataset and preprocessing

The dataset consists of nearly 42,980 mel-spectrogram data of a three-component time series from about 200 earthquakes collected from the CENA (Central and Eastern North America) and South Korea.

For the CENA, we selected the PEER NGA East database. It contains ground motion and related data such as PGA (Peak Ground Acceleration), PGV (Peak Ground Velocity), PGD (Peak Ground Displacement), and high-pass frequency from CENA (M > 2.5, with distances up to 3500 km) that have been recorded since 1976. And there are over 27k time series from 82 earthquakes and 1271 recording stations. However, the time series is a high-pass filtered, which is not appropriate for this study. Therefore, in this study, we collected the time series from the IRIS (Incorporated Research Institutions for Seismology).

For South Korea, we employed a "database of response history for historical earthquake records on the Korean peninsula" [4]. It contains over 32k ground motion data from 120 earthquakes (M >= 3.0) between 2003 and 2019. Again, it does not have time series, so we collected it from NECIS (National Earthquake Comprehensive Information System).

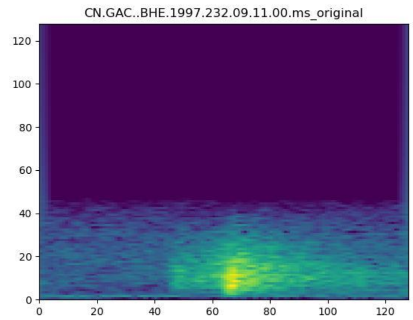

Fig. 1. 128x128 sample by mel-spectrogram

To extract features from time series, we first conduct pre-processing. 1) Consolidate the sampling rate to 100Hz 2) Convert to acceleration in the case of velocity time series 3) Remove mean and instrument response 4) Convert to physical units. Next, extract features by the mel-spectrogram. 1) Split into overlapping windows 2) Perform FFT (Fast Fourier Transform) on each window 3) Apply Mel scale and convert to Db scale 4) Arrange and stack according to time. The results have a two-dimensional shape. The number of overlapping windows is the x-axis, and the number of frequency components is the y-axis. Since the time series length of each sample is different, the x-axis length is varied. But to avoid bias during batch training, the x-axis length should be the same. So, we resized the length of the x-axis to match the y-axis. Figure 1 presents an example of a dataset sample. it consists of a two-dimensional array and has a size of 128 x 128.

2.2 Convolution Neural Network and Transfer learning

The inductive bias of the CNN model assumes that important features can be extracted from adjacent pixels. We employed CNN model to determine the frequency of the high-pass filter. We adopted ResNet [5], WRN [6], DenseNet [7], and EfficientNet [8] for this study.

ResNet using skip connections and residual mechanisms, which is easy to train and shows improved accuracy in deep networks. WRN introduced the concept of the width of residual networks and the use of dropouts. DenseNet presents direct connections between any two layers with the same feature-map size to reduce parameters and improve accuracy. EfficientNet employs compound scaling, which adjusts the depth and width of the network, reducing the number of parameters while maintaining performance.

As the network layer increases, the network can distinguish higher-level differences, making it easier to improve accuracy. However, it requires more training data to converge. To overcome these limitations, we adapted the transfer learning approach. It allows us to train the complex network despite a lack of data. In addition, we applied the C-Mixup [9] technique for augmentation data. It is a method that generates new samples by interpolating between two data samples and their corresponding labels, and the data pairs are selected by similarity criteria. This technique can improve network generalization. The CNN model selected in this study aims to solve the classification problem. However, we are dealing with a regression problem. So, we modified the last layer of the network according to the characteristics of the problem.

2.3 Training

Table I shows the summary of dataset. The dataset was split 80:10:10 into training, testing and validation, respectively.

Table I: Summary of dataset

Total	Training	Validation	Test
42,980	34,384	4,298	4,298

We used AdamW [10] as the loss function for learning. AdamW is a variant of Adam [11] that improves performance by accounting for weight decay. We adopted the 64 batch-size to train the models for 50 epochs. We also used the ReduceLROnPlateau scheduler, which reduces the learning rate if there is no improvement for a given epoch number. We employed the R^2, RMSE, and MAE to measure the accuracy and prediction error of the model.

2.4 Test Results

Figure 2 presents the accuracy during training and validation for CNN models. The dotted line and dashed line are the train and validation results. The accuracy of various models was 0.92 or higher, and ResNet showed the best performance (0.97), followed by EfficientNet, WRN, and DenseNet.

Table II: The results of CNN models in Validation set

	Best R^2	Best Loss
ResNet	0.97	0.04
WRN	0.95	0.03
DenseNet	0.92	0.06
EfficientNet	0.96	0.05

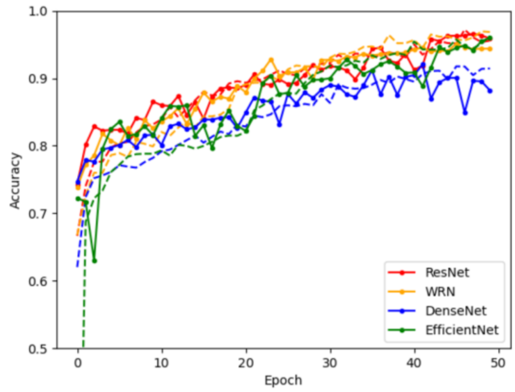

Fig. 2. Accuracy graph of CNN models in Train and Validation

Figure 3 shows the loss during training and validation. Although there were differences between the models, the accuracy and the loss improved by epoch, and the variation decreased as training progressed.

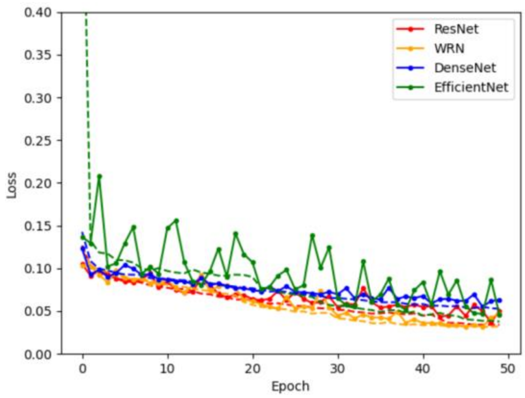

Fig. 3. Loss graph of CNN models in Train and Validation

The test set was tested using the CNN model with the lowest loss during training process. The accuracy of CNN models was evaluated using R^2, MAE, RMSE, and the results are shown in Figure 4. WRN had the best performance in the results with R^2 of 0.95, MAE of 0.20, RMSE of 0.11, respectively. The detailed results presented in Table III.

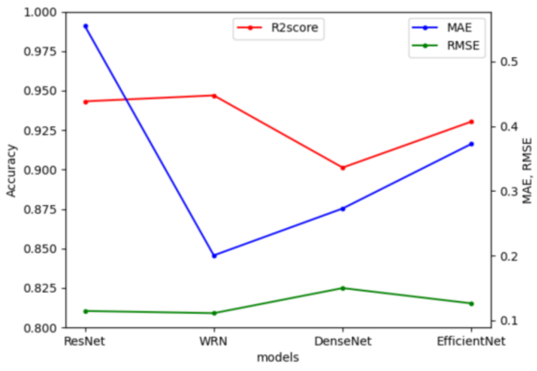

Fig. 4. Performance evaluation of CNN models

Table III: The results of CNN models in Test set

	R^2	MAE	RMSE
ResNet	0.94	0.55	0.11
WRN	0.95	0.20	0.11
DenseNet	0.90	0.27	0.15
EfficientNet	0.93	0.37	0.13

Figure 5 shows the relationship accuracy, model parameter size, and G-FLOPS (GPU Floating point Operations Per Second) for CNN models. It presented that the amount of computation increases as the model size increases. Accuracy also improved. However, the EfficientNet is an exception, which showed high accuracy despite having fewer parameters and less computation than other models.

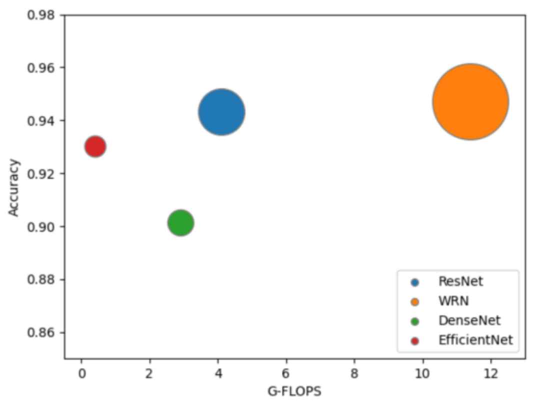

Fig. 5. Ball chart of accuracy vs. floating-point operations(G-FLOPs). The size of each ball corresponds to the model complexity.

3. Conclusions

In this paper, we studied the applicability of CNN models using mel-spectrogram to determine the high-pass filter frequency in ground motion processing. To do this, we first collected time series and high-pass filter frequency data from the CENA and South Korea. Then, we applied preprocessing such as demean, resample, and extracted the mel-spectrogram in the time series. Due to the lack of dataset, we employed C-Mixup, transfer learning, and modified pre-trained CNN models.

The ResNet, WRN, DenseNet, and EfficientNet were selected, trained, and evaluated. The test set was tested with the lowest loss during training process. The regression performances of the CNN models were compared and analyzed.

The main conclusions are as follows:

1. All CNN models presented R^2 of 0.90 or higher. The WRN model showed the highest R^2 of 0.95, and the lowest MAE, and RMSE of 0.20, and 0.11, respectively. During the training process, the losses of all models decreased, and the accuracies converged in the epoch.

2. The results presented the CNN models suitable for the high-pass filter frequency regression problem. We expect to contribute to the automation and efficiency of ground motion processing.

3. CNN models presented that the amount of computation increases as the model size increases. Accuracy also improved. However, the EfficientNet is an exception, which showed high accuracy despite having fewer parameters and less computation than other models.

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