How does a CNN mixed with LSTM methods compare with the individual one in predicting earthquakes?

Irtaza Hashmi (I.Hashmi@student.tudelft.nl)

EEMCS, Technische Universiteit Delft, The Netherlands

Abstract

Earthquakes are one of the most dangerous natural disasters that occur worldwide. Predicting them is one of the greatest unsolved problems in the field of science. In the past decade, there has been an increase in seismic monitoring stations worldwide, which has allowed us to design and implement data-driven and deep learning solutions. In this paper, we will investigate how CNN mixed with LSTM methods compare to the individual ones in predicting earthquakes given 30 seconds of seismic data before an earthquake occurs (precursor data). Preliminary results show that a CNN mixed with LSTM has the best training accuracy while an individual LSTM performs best on unseen data.

Introduction

Among natural disasters, earthquakes have the potential to cause the most damage in the shortest time. They have a destructive potential that can cause a lot of damage to the entire ecosystem of a region and may cause serious injuries or loss of human lives. An earthquake occurs when there is a sudden movement in the tectonic plates that make up the Earth's crust. The most damage is caused at the edge where the tectonic plates meet. When two tectonic plates collide and grind against each other, the stress can travel large distances and affect other regions [1]. One way to minimize the damage of earthquakes is to predict them and issue a warning in that region. This way, the region will be ready for the impact.

Problem:
Given a precursor seismic waveform, will an earthquake occur?

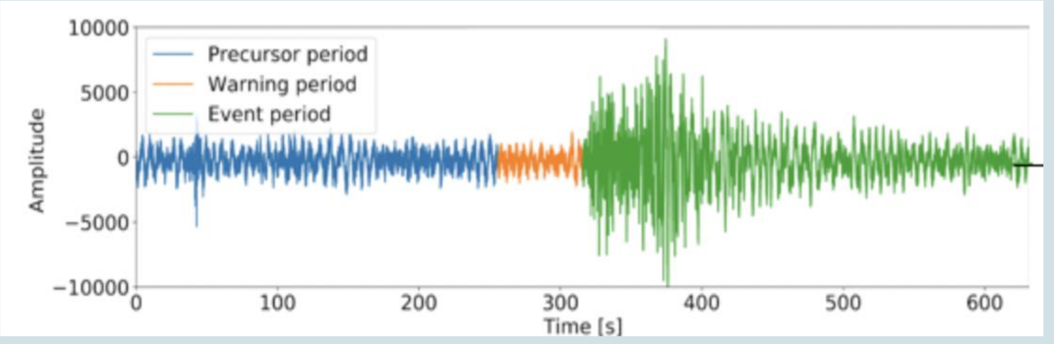

Figure 1. Event periods shown from a seismic waveform recorded by seismic geophones

Dataset

We will be using a dataset consisting of earthquakes in New Zealand from January 2016 to December 2020 provided by The International Federation of Digital Seismograph Networks (FDSN) [2]. Once we have the earthquakes data, we will retrieve the precursor seismic waveforms of 30 seconds from 58 seismic stations for each earthquake.

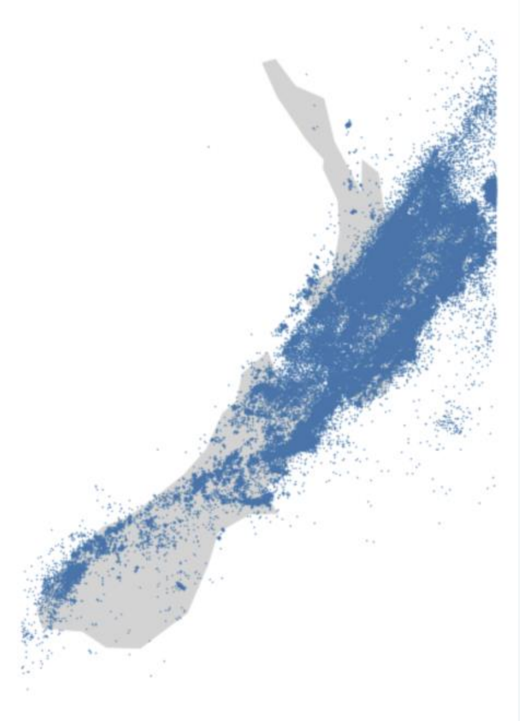

Figure 2. Earthquakes from January 2016 to December 2020. Each dot represents an earthquake on the map.

Next, we will also retrieve precursor seismic waveforms of normal behavior. The data will consist of 50% earthquake and 50% normal behavior waveforms. Only three stations are showed for simplicity.

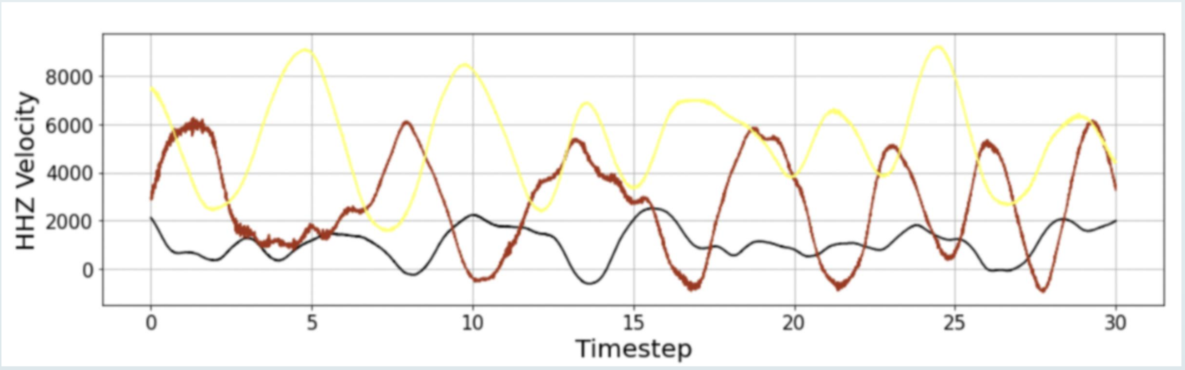

Figure 3: Precursor seismic waveforms sampled at 100 Hz.

The waveforms consist of weak motion (velocity) measured along the vertical axis at 100 Hz (100 samples per second), collected across 58 seismic stations. The earthquake occurs after the 30th timestep. As we can see, different stations have different ranges of measurements, therefore we normalized the data.

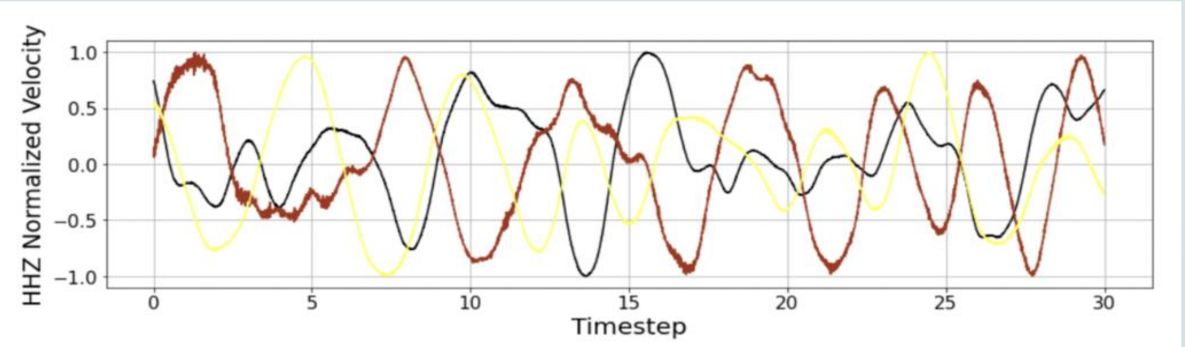

Figure 4: Normalized precursor seismic waveforms per each station.

Deep Learning Approach

Three different deep neural networks were investigated to see which performs best. The first model was an **individual CNN**. It had two layers with filters = 128 and a dropout rate of 0.5. The model has a batch size of 64.

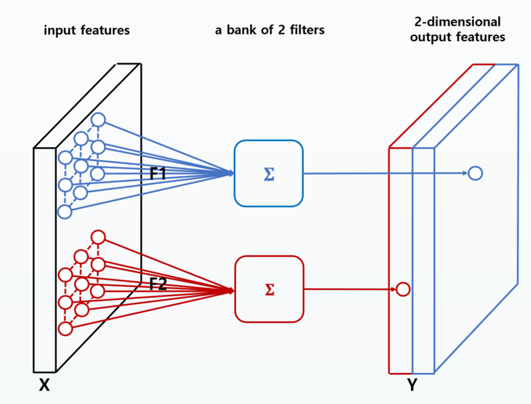

Figure 5. CNN model architecture

The second model was an **individual LSTM**. It had 60 neurons and a dropout rate of 0.4. The model has a batch size of 64.

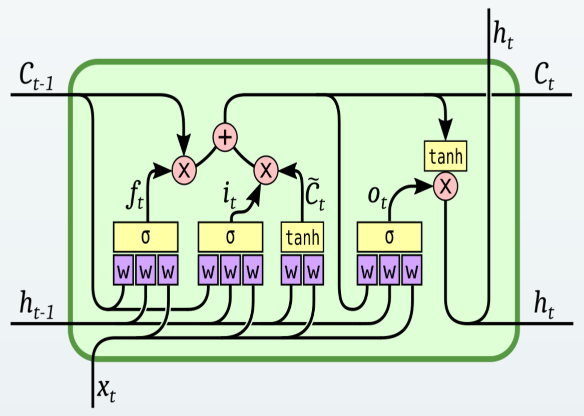

Figure 6. LSTM model architecture

The third model was **CNN combined with LSTM.** It has 3-layers of CNN with 128 filters to extract features in the seismic data. Next, it has 3-layers of LSTM to recognize and remember time patterns with 128 neurons and a dropout rate of 0.6. The model has a batch size of 256.

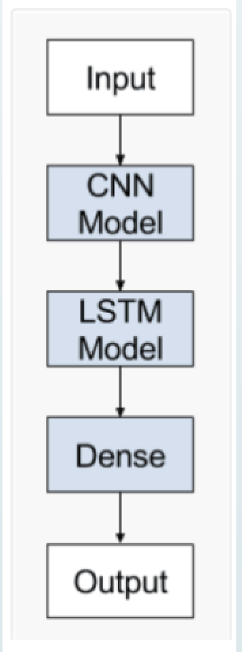

Figure 7. CNN-LSTM model architecture

The model was trained on **2, 5, 10, 25, 50 and 100 Hz** precursor data to see if frequency had any relation with performance.

Results

Table 1. Performance evaluation metrics

Performance Evaluation Metrics for CNN, LSTM, and CNN-LSTM			
Metric Type	CNN	LSTM	CNN LSTM
TP	1874	2227	2470
TN	2541	2266	2039
FP	1889	2164	2391
FN	2530	2177	1934
S_n	0.426	0.506	0.561
S_p	0.574	0.511	0.460
P_0	0.501	0.510	0.513
P_1	0.498	0.507	0.508
Training Accuracy	0.718	0.745	0.858
(Test) Accuracy	0.511	0.513	0.510
Average Accuracy	0.538	0.549	0.568

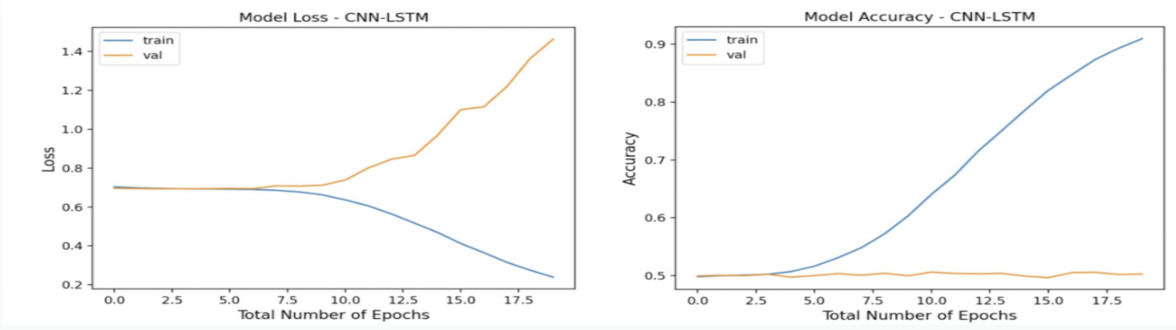

Figure 8. CNN model loss (left) and accuracy (right)

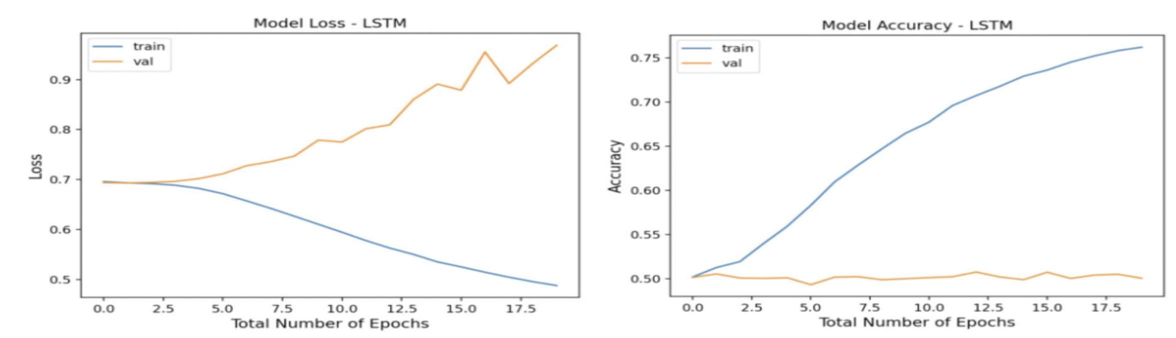

Figure 9. LSTM model loss (left) and accuracy (right)

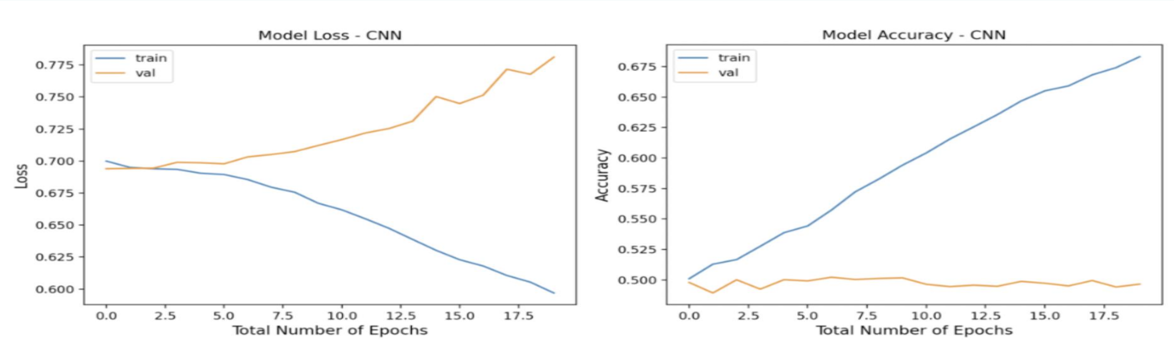

Figure 10. CNN-LSTM model loss (left) and accuracy (right)

Conclusion

- CNN-LSTM model is the best out of the three in predicting earthquakes
- CNN model is the best in predicting normal behaviour
- The CNN-LSTM had the best training accuracy
- LSTM had the best test accuracy
- **CNN-LSTM performed the best out of the three models with an average accuracy of 0.568**

Limitations

- The number of events currently used to train the models may not be enough for this problem

Future Work

- Research and investigate more machine learning and deep learning techniques for this problem
- Experiment with larger and cleaner datasets

References

1. M. Moustra, M. Avraamides, and C. Christodoulou, "Artificial neural networks forearthquake prediction using time series magnitude data or seismic electric signals,"Expert Systems with Applications, vol. 38, no. 12, pp. 15032–15039, 2011.

2. https://www.geonet.org.nz/data/tools/FDSN