Impact of Focal Depth on Short-Term Earthquake Prediction using Deep Learning

Pijus Krisiukenas
Supervisors: Elvin Isufi, Mohammad Sabbaqi
EEMCS, Delft University of Technology, The Netherlands

June 19, 2022

A Dissertation Submitted to EEMCS faculty Delft University of Technology,
In Partial Fulfilment of the Requirements
For the Bachelor of Computer Science and Engineering

Abstract

Due to the devastating consequences of earthquakes, predicting their occurrence before the first strike has been a long standing research topic. Deep learning models have been used to facilitate prediction, using seismograph data to attempt to classify an earthquake right before it happens. However, this is a difficult task and research needs to be conducted into how properties of earthquakes impact the accuracy of models. Thus earthquake focal depth was studied as a factor in prediction accuracy, specifically comparing deep and shallow earthquakes, split along a depth of 70km. An LSTM model was trained using these different data sets, providing 30 seconds of seismic waveform data and given the task to predict the occurrence of an earthquake 3 seconds in the future. Training this model 20 times with each data set resulted in the accuracies of 0.869 for shallow earthquakes and 0.850 for deep ones. Thus the results show that both shallow and deep earthquake trained models performed similarly well.

1 Introduction

The ability to predict earthquakes has been a long standing goal for researchers [1], as the ability to mitigate and prevent earthquake damage has major societal implications. Prediction efforts have focused on two main types of earthquake prediction, which are short-term and long term [2]. Short-term prediction allows for early warning of an earthquake about to happen. This type of prediction, however, has proved to be a difficult task, due to the large number of factors that influence the generation of earthquakes [3]. To accommodate complexity, machine learning models and specifically deep learning models have been studied for their potential to learn patterns in such data. The goal of prediction using deep learning is to classify a seismic wave moments before the strike, given some duration of preceding seismic recordings. There have been multiple methods proposed for use in earthquake prediction, like convolutional neural networks [4] and recurrent neural networks, which were specifically developed to deal with sequences of data. Further research produced an improved variant called "long-short term memories", shortened as LSTM [5]. An LSTM based model has been able to predict the presence and location of an earthquake with 86% accuracy [6].

Focal depth is an important characteristic of earthquakes, often analyzed in geoscience. Based on this property, earthquakes can be classified into three main groups: shallow, intermediate, and deep. There are differences between these types of earthquakes [7], especially in the received seismographic signal strength [8]. This may be a source of differences in how well machine learning models can perform in detecting shallow or deep earthquakes. Because earthquakes of differing depths have been shown to influence each other [9], training models on different depth data can be useful in increasing the accuracy of overall earthquake prediction.

There has been research conducted into how deep learning can be used for determining the focal depth of an earthquake [10]. There is, however, no research into the topic of how depth can influence the performance of an earthquake prediction model. Therefore this paper will take information gathered from more distant research topics and theoretical applications from the field of geoscience. Furthermore, to train the models there is also need for a data source, with one option being time series data at multiple measuring stations from the GeoNet New Zealand data set [11]. This data source is free and extensive, also being used in previous research like "Graph-Time Convolutional Neural Networks" by G. Mazzola [12]. While the goal of this paper and model used are different, the data pre-processing and analysis steps that were taken in previous research can be applied to this paper.

To fill the gap in currently available research, the purpose of this research paper is to analyze the difference depth makes in earthquake prediction, with the main research question of *"Can deep learning techniques detect better shallow earthquakes or deeper ones?"*. To answer this question the Geonet New Zealand data set will be used [11], with deep learning model chosen to be LSTM [5], which is commonly used in previous research. As deep earthquakes are harder to detect and the received seismic signal is weaker [8], a hypothesis is proposed that a deep earthquake trained model will perform worse. The following sections of the paper will detail how the research was conducted. Section 2 will present the process and methods of setting up the experiment. Then in Section 3 the data set and its preprocessing are presented, together with the architecture of the model. Further in Section 4 the results of evaluating the model are presented, with Section 5 discussing the topic of responsible research. Finally, in Section 6 the conclusion of the research is presented, then a discussion the possible causes of the result, comparing to existing knowledge and expectations, then providing possibilities and guidelines for further research.

2 Methodology

The research question will be answered by defining a model that performs short-term classification, splitting the data set based on depth, and then training a model on these different sets. The training data will be equal for both depths, also containing an equal number of background data, where no earthquake will happen in the near future. This will be referred to as "normal" data. After training both models are evaluated and compared, thus deciding if the model is better at detecting shallow or deep earthquakes. The model will be given 30 seconds of seismic waveform data before an earthquake takes place. This length was chosen due to the sufficient amount of samples that can be attained in this period, while also not being too far away from the earthquake happening that there is too much background noise. The output is a binary classification of the input signal, indicating the occurrence of an earthquake three seconds in the future.

2.1 Deep learning models

The deep learning model that will be used for training and evaluation is a "Long-Short term memory" [5], which is a type of a Recurring neural network (RNN). RNNs differ from regular multi-layer neural networks by taking a series of inputs, with each sample being processed one by one. Then the output of processing one of the samples is used for calculating the output for the next in the series. They do suffer from a problem called vanishing and exploding gradient [13], where the parameters of the model either tend to "explode" and attain large values or tend towards zero. This causes instability and training issues. The model LSTM improves on this by introducing a forget gate, which limits what the model remembers, while the cell state facilitates the propagation of long-term memories. A graph showing the full model of an LSTM can be seen in Figure 1

Therefore, due to their ability to deal with time-series data and common use in the field of earthquake prediction [6], this is a valid choice specifically for the task of earthquake prediction.

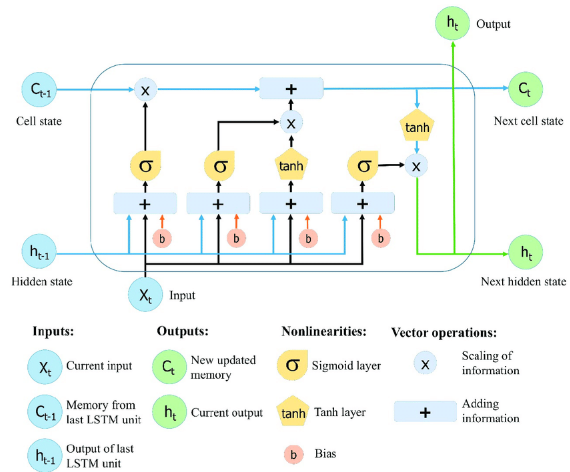


Figure 1: LSTM architecture [14]

2.2 Definition of shallow and deep earthquakes

To answer the main research question and split the data set for training models, there needs to be a concrete definition for where the separation between deep and shallow earthquakes is. The United States Geological Survey provides this definition, saying:

> *"For scientific purposes, this earthquake depth range of 0 - 700 km is divided into three zones: shallow, intermediate, and deep. Shallow earthquakes are between 0 and 70 km deep; intermediate earthquakes, 70 - 300 km deep; and deep earthquakes, 300 - 700 km deep."* [8]

An example of these depth regions can also be seen in Figure 2.

The presented definition presents a practical problem: earthquakes below the depth of 300km are very hard to detect and are rarely recorded [7]. Confounding that, from the available data most recorded earthquakes have a shallow depth. Due to this imbalance in data, a comprise is made to include intermediate earthquakes as part of the "deep" earthquake set. Therefore, shallow earthquakes are defined as those occurring in depths of 0-70 kilometers, while earthquakes happening in the 70-700 kilometer depth range are considered deep.

2.3 Analysis metrics

The output of the model is a binary digit, either 0 or 1, with 1 indicating the occurrence of an earthquake and 0 not. This output model has 4 possible outcomes in regard to data prediction:

1. True Positive(TP): the data showed an earthquake happening (1) and the model predicted 1
2. False Positive(FP): the data indicated lack of an earthquake (0), while the model predicted 1

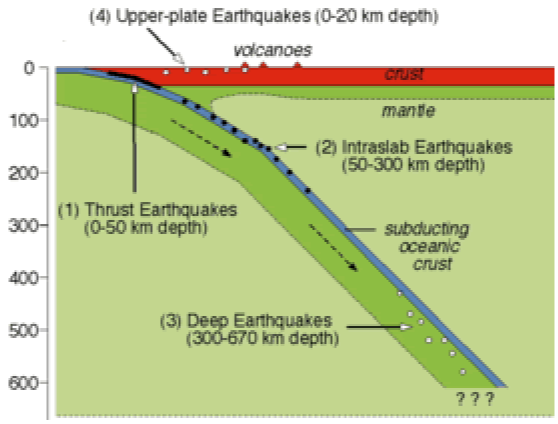


Figure 2: Earthquake depth diagram [15]

3. True Negative(TN): the data and model prediction both indicated 0
4. False Negative(TN): the data showed 1, while the model predicted 0

A good model attempts to maximise both True Positives and True Negatives while minimizing False Positives and False Negatives. For earthquake prediction, False Negatives is the main focus, due to the damage that earthquake can cause if they are not prepared for. False Positives are also of concern, as common mispredictions will create annoyance and distrust of the detection system. Thus both measures can be considered as important for evaluating the effectiveness of the model. Therefore, multiple metrics are used. First is the most general purpose metric of accuracy, which considers both false predictions. It is calculated using this formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

To account for False Positives and False Negatives separately, the precision and recall metrics are used, which are calculated as such:

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

3 Implementation

This section will detail the data preprocessing steps taken, define variables and specify model implementation, which is then used for evaluation.

3.1 Data preprocessing and analysis

The data source used was earthquake seismographic measurements from the New Zealand data set [11]. This source compromises 539 stations in total, located in New Zealand. To standardise location, a bounding box of the retrieved data was defined between the latitudes of -47.749 and -33.779, and longitudes between 166.104 and 178.990. Default parameters were kept for the location and channel, which were *10* and *HHZ* respectively. The label

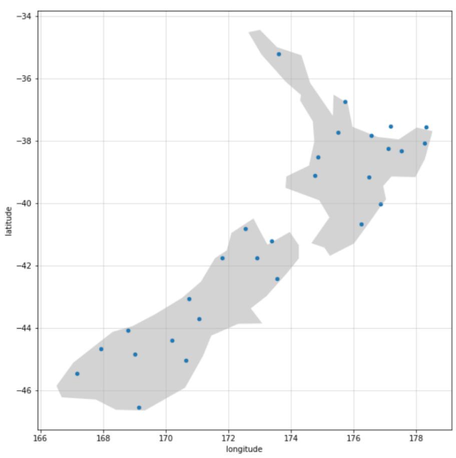


Figure 3: Locations of selected 28 stations

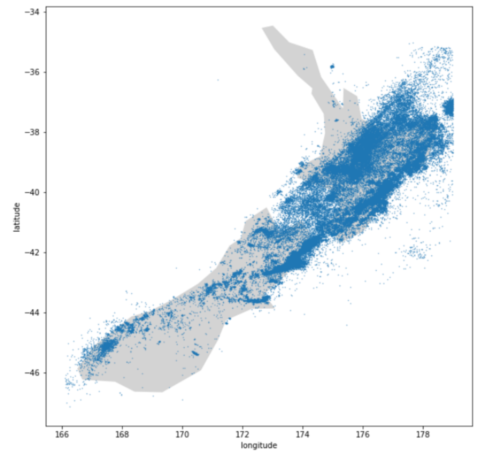


Figure 4: Locations of selected earthquakes in the period 2016-01-01 to 2020-01-01

HHZ is a way to encode the specific channel wanted from a data service, with this code selecting a high broadband, high gain seismometer in the Z orientation [16]. The default channel was kept as this paper considers seismic waveforms for prediction, while the high broadband is used due to it having " high sensitivity over a very wide dynamic range" [17], which allows for accurate measurement of a wide range of magnitudes and captures the natural high frequency noise that occurs before and during earthquakes.

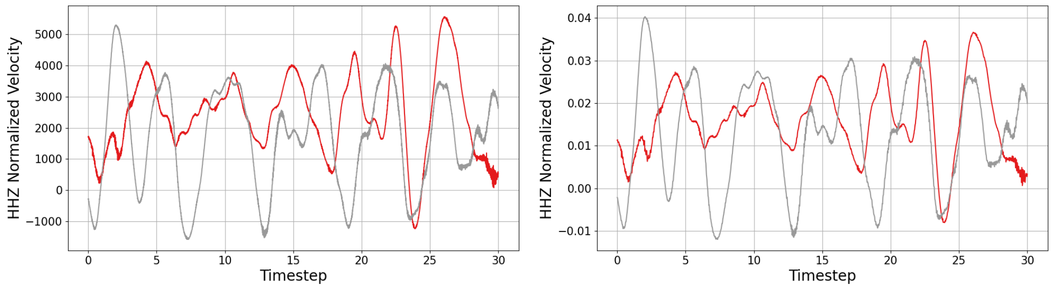
3.1.1 Station filtering

Due to an imbalance in where earthquakes happen (see Figure 4), different regions in New Zealand have a larger concentration of stations. This could potentially cause imbalance issues when training the model and there is limited use to be gained from using a signal from very close stations. Therefore, the location code of 10 was used to retrieve a list of 91 stations, that are mostly equally distributed over New Zealand.

However, there were major differences in data integrity and signal differences. This pattern meant that some stations performed significantly worse [18], so there had to be a second step to identify these stations and remove them from the data set. This was achieved at a later stage by using a basic model and training it on the stations individually. Then the stations with close to guessing accuracy (50%-53%) were removed. This results in 28 final stations, which can be seen displayed over a map of New Zealand in Figure 3, while a full list of them can be seen in Appendix A.

3.1.2 Earthquake filtering and background data selection

To reduce the amount of data to a manageable number, events were taken from the period 2016-01-01 to 2020-01-01. To ensure all earthquakes could be detected by the selected stations, events were filtered such that they were all within 270km of one of the stations. This leaves 99268 events. For final processing, magnitude outliers are removed, keeping only earthquakes with magnitudes above 1 and below 3. This step was done to remove low mag-



(a) Original waveform

(b) Processed waveform

Figure 5: Comparison of two original and processed waveforms

nitudes that are barely distinguishable from background noise and to ensure a few outliers with a significantly different magnitude do not reduce model accuracy. The final number of events considered therefore is 88740. These final earthquakes can be seen plotted in Figure 4.

To accompany the data retrieved before earthquakes, an equal number of background noise samples have to be retrieved. This data was downloaded by taking 30 seconds of waveforms 1000 seconds before an event, for each event. This does have a possibility of including an earthquake in the retrieved waveform, but due to the rarity of earthquakes, it was presumed to make a minimal impact on the data set.

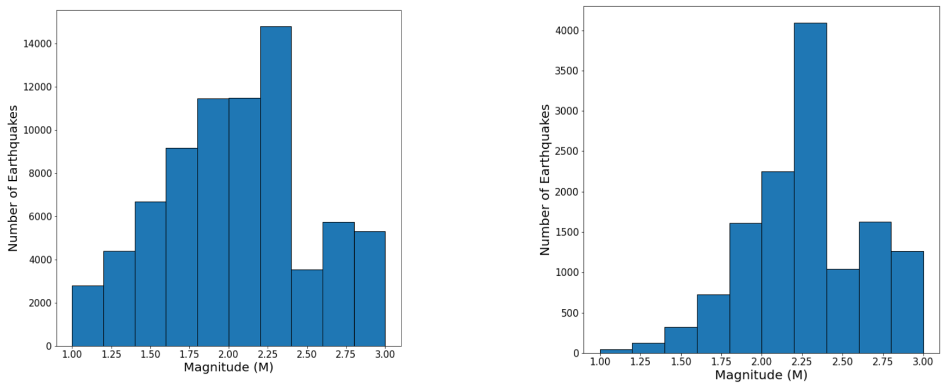
3.1.3 Waveform processing

The received waveforms are the vertical velocity recording during a set period, either before an earthquake or not close to any. The sample rate of the recording is 100HZ, meaning a total number of discrete numbers (samples) of 3000, which is quite high quality for the prediction workload. To reduce the impact of noise and improve model performance, down sampling is used, specifically decimating the signal by omitting every nth sample. To retain some noise that occurs during/before earthquakes a down-sampled rate of 50HZ was chosen. Therefore the final number of samples per recording was 1500.

To ensure proper functioning of the model used, the data was normalized in the vertical velocity axis. Initially, both l2 normalization and min-max scaling was used, but scaling was found to provide significantly worse result when used for training. Therefore, only individually applied l2 normalization was used, limiting all values in the range of [-1,1]. Some data in the downloaded waveforms was found to be corrupted, therefore waveforms containing some corrupted values (-14822981 or 14822981) were removed from the final set. A comparison of two waveforms before and after processing can be seen in Figure 5.

3.1.4 Final data set

To ensure fairness in trained model comparisons, both shallow and deep data sets should contain an equal number of events. Due to the imbalance of depth in the data set (see Figure 7), the smaller set was the deep one, being in total 14192 events. All earthquakes that were classified as deep were retrieved, while only a partial number of shallow earth-



(a) Magnitude distribution of shallow earthquakes

(b) Magnitude distribution of deep earthquakes

Figure 6: Comparison of deep and shallow earthquake magnitudes

quakes were downloaded. To ensure equal date-time distribution of the limited set (shallow earthquakes), events to be downloaded were selected randomly and uniformly over the time window of 2016 to 2019.

No further normalisation between the data sets was performed, so imbalances in the properties of the waveforms are maintained as close to real life. An example of this difference, showing the distribution of magnitudes of these sets, can be seen in Figure 6. It can be noted that deep earthquakes have a much lower number of low magnitude samples. This is due to the distance that the earthquake foci have from measuring stations, therefore the received signal is weaker than that of a shallow earthquake.

Due to filtering processes taken and missing station data, the final amount of data used for training was reduced by around half. Thus the number of events used for training was 8037, equal for both deep and shallow sets. The input data is also appended with an equal number of normal data.

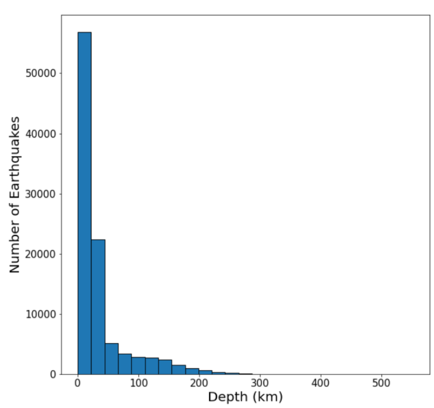


Figure 7: Distribution of earthquake depth in the data set

3.2 Model

The input of the model is a two-dimensional matrix (28, 1500), containing 1500 waveform samples for each of the 28 stations. A single layer LSTM is used, which has a hidden neuron size of 16. The data is therefore transformed from a two-dimensional matrix into a one-dimensional list of size 16. A ReLU activation function is used, which is then connected to a traditional fully connected layer. This layer transforms the list of values into the same shape as the label, which is a single digit. Then the sigmoid activation function provides the final prediction within the range [0,1]. As the labels are binary, the predicted value of the model was rounded to the nearest label, thus values below 0.5 were treated as 0, and those above 0.5 were treated as 1. A visualisation of the described model used can be seen in Figure 8.

3.2.1 Over-fitting

Due to the nature of the data used for training the model, there is a lot of noise in the waveforms. This can cause over-fitting, where the model tries to fit the training data too accurately. To prevent over-fitting, a dropout layer was used [19]. The dropout layer was applied after the LSTM layer. Previous research indicates that for the probability of dropout, values in the range 0.1 to 0.8 provide the best results. However, big values cause the model training to take more epochs before converging, moreover the model used in this paper is rather small. Therefore, a lower end value of 0.1 was used.

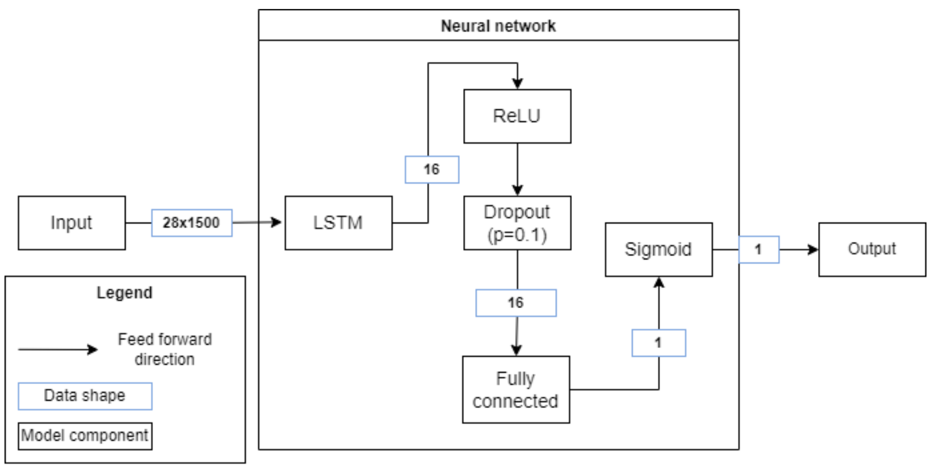


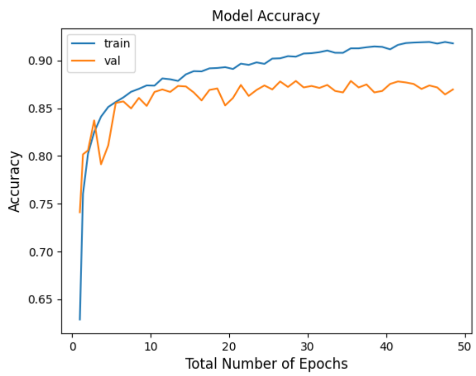
Figure 8: Model graph

4 Experimental Setup and Results

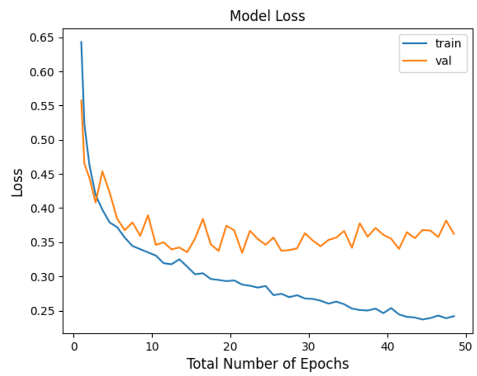
Using filtered data of both deep and shallow earthquakes, two models were trained. The models were trained for 100 epochs, with a batch size of 32. The Adam optimiser [20] was used, with a learning rate of 0.001.

The data was split into three parts: training, validation, and test sets. Their distribution was 70%, 10%, and 20% respectively. After each epoch, both training and validation set accuracy and loss of the model were reported. At the end of the training, the accuracy, recall and precision of running the model on the test set was also tracked.

Their training history, showing accuracy and loss over time, can be seen in Figure 9 for the shallow model, and Figure 10 for the deep model.

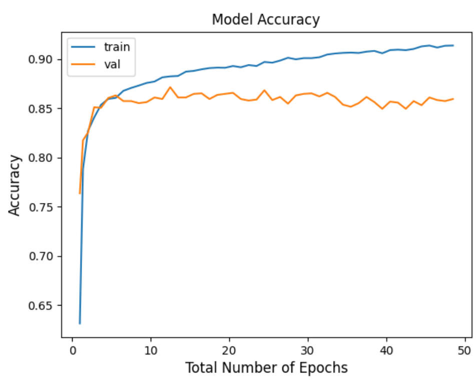


(a) Training and validation accuracy curve

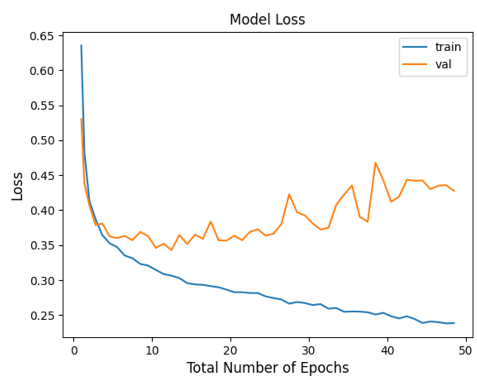


(b) Training and validation loss curve

Figure 9: Shallow earthquake learning curves for 50 epochs



(a) Training and validation accuracy curve



(b) Training and validation loss curve

Figure 10: Deep earthquake learning curves for 50 epochs

To compare these models fairly and reduce randomness from the training process, each model was trained 20 times, collecting the final test accuracy, precision, and recall. The results of this comparison can be seen in Figure 11. Mean accuracy and standard deviation of these runs were calculated and can be seen in Table 1.
From the multiple analysis metrics used, it can be concluded that both shallow and deep earthquake models performed similarly well. Training history graphs in Figures 9 and 10 show no apparent difference in how the model fits the data sets. The averaged results of multiple trained models seen in Table 1 also show a minimal difference in accuracy, with the shallow mean having an accuracy of 0.869, compared to 0.85 of the deep mean. Recall

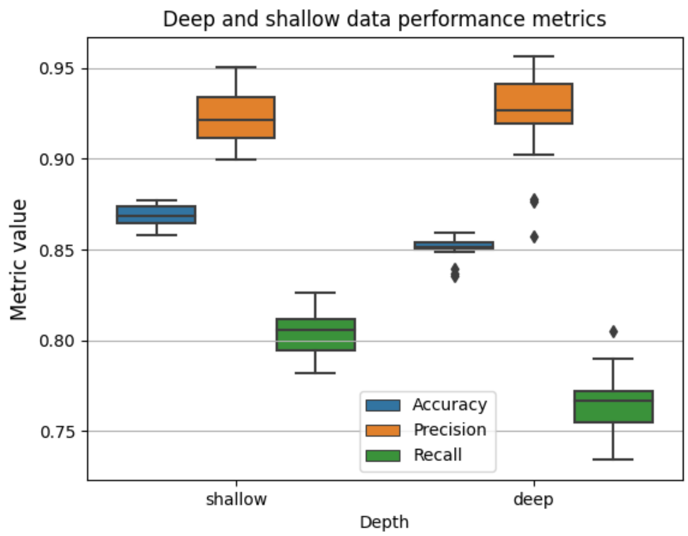


Figure 11: Box plot of test accuracy, precision, and recall. Collected from the same model trained separately 20 times.

	Shallow			Deep		
Metric	Accuracy	Precision	Recall	Accuracy	Precision	Recall
Standard Deviation	0.006	0.014	0.012	0.006	0.026	0.017
Mean	0.869	0.924	0.804	0.850	0.923	0.766

Table 1: Comparison of shallow and deep model mean accuracy and standard deviation

and precision followed a similar pattern of a very slightly smaller mean for the deep data compared to shallow. Standard deviations were also similar, with a slight relative difference.

Both models had a much higher precision compared to recall, meaning a higher number of false negatives than false positives. This implies some of the low magnitude earthquakes are difficult to distinguish from background noise, so given the larger number of background noise samples compared to low magnitude events, the model is more likely to predict 0. The models also showed a more noticeable difference between recall means, showing that deep earthquakes are less differentiable from background noise.

5 Responsible Research

With deep learning research, it is important to consider the pitfalls of what such models can cause. There is great benefit to be gained from the ability to accurately and reliably predict earthquakes before they happen, so much so that this was investigated before prediction was truly feasible [1]. However, even if it was possible, machine learning models in principle should not be fully trusted. In nature, they are probabilistic and can often show better results in a controlled environment than in a realistic one. Thus, caution should be taken when relying on these models for real world use.

The research conducted was detailed as specifically as possible, so that the results received could be re-produced. The data used is open source and be accessed for free from the GeoNet website [11]. The pre-processing parameters and steps are detailed in Section 3.1, while the model is described in Section 3.2, with hyper-parameters used for obtaining the results described in Section 4. Using these steps, a student that is familiar with machine learning, python, and a library for using machine learning (TensorFlow, PyTorch) can also conduct the same research. To ensure reproducibility and limit issues with specific implementation details, the code used for this research is available online [21].

6 Conclusion and Discussion

This study analyzed the question of if shallow or deep earthquakes are better suited for short-term deep learning prediction. Data was used and pre-processed from GeoNet, covering stations in New Zealand. Two data sets were created, separating deep and shallow earthquakes in each, split along the depth of 70km. An LSTM model took 30 seconds of input and tried to predict the occurrence of an earthquake 3 seconds in the future. Each model used an equal number of active samples, with an equal number of background, non-active samples. The models were evaluated by training them 20 times and comparing the final mean test accuracy, recall and precision. The results showed a very similar accuracy for both models, with an accuracy of 0.869 for the shallow one, compared to 0.850 for the deep one. Thus, it can be concluded that deep learning techniques are similarly capable of predicting both shallow and deep earthquakes.

The attained result was different than what was hypothesised. The original expectation was the model trained on deep earthquake data will under perform to that of a shallow data trained model, with actual results showing little difference. There are a few possible explanations for why the difference observed was minimal and previous presumptions did not hold. Firstly, the number of samples used was equal for shallow and deep earthquakes, thus removing the real world imbalance in the number of recordings for the sets (see also Section 3.1.4). Further, from Figure 6 it can be seen that deep earthquakes have a much lower number of low magnitude samples. However, the magnitudes are more uniform, so this could explain the ability of the model to find patterns similarly well between the data sets.

The overall model accuracy attained follows in line with what was previously observed in some research [6], but higher than what was previously achieved using an LSTM and the same data set [18]. The mean accuracy was lower, while the maximum value attained was quite similar to the one reported in this paper. This difference can be explained by data processing, as the mentioned paper selected stations differently. Moreover, the model was only trained using data from a single station at a time, thus limiting the total number of samples per model. Finally, normalisation of waveforms was different, using min-max scaling with a single 30-second waveform at a time, compared to l2 normalization.

The conclusions of this paper can guide further research into improving model accuracy and the factors that influence it. Even considering the lack of difference focal depth makes in prediction accuracy, there is use in splitting data based on depth and training models separately [9].

The results presented do have limitations for general conclusions for all cases. Due to limited research in this field, different approaches have to be taken to test the generalizability of the research. Most importantly, data from different sources and regions should also be considered, as different earthquake prone regions contain possibly unique types of tectonic processes. The events used were also limited to a certain magnitude range, so considering earthquakes in different magnitude ranges could reveal different patterns. Further, the model used could also potentially have an effect on how different data is treated, thus the method presented could be extended for use for many models. Finally, data pre-processing is a complex matter in the field of signals, especially natural ones. Different steps taken and values used in down sampling, normalization and could introduce more significant differences in the signal used for final training. Finally, the preprocessing steps taken regarding station filtering in Section 3.1.2 were done using a draft model by comparing accuracies achieved. Therefore, this processing step is model dependent, and depending on hyper parameters and specific deep learning model used, the final station list could be different.

Acknowledgments

I would like to thank my research project group mates for collaboration on research. I would also like to credit Kevin Zhu for providing ideas and code base to develop from for data preprocessing and an LSTM model.

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A Appendix A

Station Code	Longitude	Latitude	Site
BFZ	176.246245098	-40.679647283	Birch Farm
BKZ	176.492543736	-39.165665643	Black Stump Farm
DCZ	167.153533463	-45.464713192	Deep Cove
DSZ	171.804614445	-41.744960821	Denniston North
HIZ	174.855686101	-38.51292897	Hauiti
JCZ	168.785473425	-44.07321036	Jackson Bay
KHZ	173.53897	-42.41598	Kahutara
KUZ	175.720872942	-36.745228533	Kuaotunu
LBZ	170.184419859	-44.385552844	Lake Benmore
MSZ	167.92639864	-44.673333781	Milford Sound
MWZ	177.527779304	-38.334001396	Matawai
MXZ	178.306631253	-37.562258507	Matakaoa Point
NNZ	173.379476754	-41.217102661	Nelson
ODZ	170.644622213	-45.043982113	Otahua Downs
OPRZ	176.554929138	-37.844300073	Ohinepanea
OUZ	173.596133449	-35.219688708	Omahuta
PUZ	178.257209049	-38.071547867	Puketiti
PXZ	176.862145221	-40.030644463	Pawanui
QRZ	172.529147829	-40.825521618	Quartz Range
RPZ	171.053864882	-43.714607582	Rata Peaks
SYZ	169.138823018	-46.536890349	Scrubby Hill
THZ	172.905218304	-41.762474128	Top House
TOZ	175.501846822	-37.73095563	Tahuroa Road
URZ	177.110894471	-38.259249093	Urewera
VRZ	174.758452563	-39.12434088	Vera Road
WIZ	177.189301882	-37.524510539	White Island
WKZ	169.017561979	-44.827021353	Wanaka
WVZ	170.73675416	-43.074350291	Waitaha Valley

Table 2: Final list of stations used