AETA Earthquake Prediction

CSE 572 Data Mining Final Project

Chen Ni Lin†
School of Computing and Augmented Intelligence
Arizona State University
Tempe Arizona USA
clin250@asu.edu

Chang Guo
School of Computing and Augmented Intelligence
Arizona State University
Tempe Arizona USA
cguo51@asu.com

Jiahui Li
School of Computing and Augmented Intelligence
Arizona State University
Tempe Arizona USA
jiahui12@asu.com

John Kevin Cava
School of Computing and Augmented Intelligence
Arizona State University
Tempe Arizona USA
jcava@asu.edu

ABSTRACT

Earthquakes pose a threat to humanity due to the increasing expansion of human civilization into earthquake-prone areas, especially around the "ring of fire". Many of these earthquakes are perceptually undetectable by humans. Consequently, there are countless seismographs around the world to record the various magnitudes of earthquakes. To process and make predictions from data-rich sensors, it is important to create an automated system that can stream the data and give real-time predictions. Previous work has revolved with anomaly detection, clustering, and using time series methods like LSTMs to predict the magnitude of a possible future earthquake. However, real data is mostly noisy, and thus may affect the model for future predictions. Currently, there is no work on comparing noisy-tolerant models like Noisy-RNN for real sequential data such as AETA Earthquake Prediction Competition.

KEYWORDS

AETA, Earthquake prediction, CNN, LSTM, RNN, Noisy-RNN

1 Introduction

Earthquakes are not a very rare natural phenomenon. The magnitude of an earthquake can range from small earthquakes to large, disruptive events that cause significant damage to buildings and infrastructure and loss of life. In 2023, two earthquakes measuring 6.4 and 5.8 on the Richter scale occurred on the Turkish-Syrian border. The total death toll in Turkey has exceeded 41,000 and 1.5 million people have been left homeless. In northwest Syria, as many as 9 million people have been affected and at least 6,000 have lost their lives. This is despite a variety of traditional prediction methods, including seismic monitoring, tomographic mapping, satellite monitoring, and animal behavior monitoring. But none of these methods can predict earthquakes accurately enough to prevent damage and loss of life. And these methods have their own limitations, such as the inability to accurately predict earthquakes, and these methods are difficult to predict the time and magnitude of earthquakes. As a result, new and more accurate predictive models are needed to improve earthquake preparedness and response.

Machine learning techniques provide a more efficient method of earthquake prediction because machine learning models can analyze large amounts of earthquake data, including historical earthquake records, in a relatively short period of time. This allows researchers to identify patterns and correlations that human analysts may not be able to spot immediately. By integrating multiple types of data from a variety of sources, such as geological and geodetic data, machine learning models can gain a more complete picture of the factors driving seismic activity and make more accurate predictions. Second, machine learning models can model the complex relationship between seismic activity and a range of environmental factors, such as changes in temperature, rainfall, and groundwater levels. As a result, machine learning models can provide more accurate earthquake predictions than traditional methods, such as predicting the time, place, and magnitude of earthquakes, reducing the impact of earthquakes on infrastructure, property, and human life.

Commonly used machine learning techniques in earthquake prediction research include neural networks, support vector machines, and random forests. Neural networks can identify patterns and correlations in large datasets. In earthquake prediction research, neural networks are often used to analyze earthquake data and identify earthquake precursors. Support vector machines are often used to analyze geodetic data to identify areas of high seismic risk. Random forests are often used to predict earthquake magnitude and location based on historical earthquake data and environmental factors.

In this project, we will use a total volume of 38TB dataset, which includes station data, electromagnetic disturbance data, and geoacoustic data from January 1, 2017 to April 30, 2022. Time interval of the target area is the ten-minute granularity of all stations in the Sichuan-Yunnan region of the AETA observation network.

To reduce the dimension and extract useful features from the original dataset, Convolutional Neural Networks (CNNs) are employed as a feature extraction tool. Noisy-RNN is chosen as the classifier due to its robustness against noise and missing values in the input data. Evaluation metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC) are used to assess the performance of the classifier. The study shows that the proposed Noisy RNN model outperforms other machine learning methods such as SVM and CART decision tree in earthquake prediction. As shown in the experiments. The final model achieves an accuracy of 0.7661, a precision score of 0.6423, a recall score of 0.7384, an F1-score of 0.0655, and an AUC of 0.702.

2 Related Work

Earthquake prediction has been an active research area, and several studies proposed to utilize machine learning methods to finish this task. Wang et al. [1] and LI et al. [2] both focus on earthquake prediction models using long short-term memory (LSTMs) [6] based techniques. Trugman et al. [10] present a data-driven machine learning method and use convolutional neural networks (CNNs) to extract features. Perol et al. [12] also presents a CNN-based approach for automatic earthquake detection using raw seismic data. Ross et al. [11] and Zhang et al. [13] combine CNNs and recurrent neural networks (RNNs) to extract spatiotemporal features from the data and train the network to detect and locate earthquakes. Zhang et al. [4] combines LSTM with CNN to capture both spatial and temporal features in the seismic data. Asim et al. [17] apply multiple machine models to analyze the earthquake features. Asim also sends Linear Programming Boost to the classifiers to show better results, like sensitivity. However, a limitation in these studies is the lack of standardized datasets, making it challenging to compare results.

Bi-directional block self-attention algorithm (BBSA) [8] is introduced to improve memory usage and computational efficiency. BBSA divides the sequence into blocks and applies self-attention within each block and between adjacent blocks. Clustering algorithms have also been explored to monitor wireless sensor networks. Ma et al. [9] propose a density-based clustering algorithm to improve data transmission efficiency and accuracy. Graph neural networks (GNNs) [15] is used to multivariate time series regression with seismic data, incorporating spatial relationships between seismic nodes, but the accuracy of this framework heavily depends on the accuracy and capacity of the CNN feature extractor.

For feature extraction and analyzing, Schaff and Richards [5] propose a waveform similarity-based method, while Perol et al. [12] use high-frequency amplitude ratios to process sparse data from a single array. However, these methods are specific to single arrays and may not be widely applicable.

Researchers have also explored various neural network architectures to improve earthquake prediction. Lim et al. [3], Zhu et al. [7], Rubanova et al. [14], and Adeli et al. [16] propose techniques like incorporating structural knowledge.

3 Background and Motivation

3.1 Earthquake

The earthquake is a natural phenomenon that occurs when tectonic plates move and shift, causing energy to be released and resulting in ground shaking and vibrations. These vibrations are called seismic waves, which can cause damage and destruction to buildings, infrastructure, and other structures. Earthquakes are typically measured using the Richter scale, which assigns a numerical value to the intensity or magnitude of the earthquake. The scale ranges from 1 to 10, with each increment representing a ten-fold increase in earthquake strength. For example, a 6.0 magnitude earthquake is ten times stronger than a 5.0 magnitude earthquake. Earthquakes can cause various types of damage and destruction, the severity and extent of which vary due to a range of factors.

One of the most common types of earthquake damage is building damage. Structures that are not designed to withstand seismic activity may suffer severe structural damage or even collapse. Infrastructure damage is also a common result of earthquakes. Roads, bridges, and public utilities may be damaged, making it difficult for emergency responders to reach affected areas and disrupting basic services such as water and electricity. Earthquakes can trigger landslides and tsunamis, causing significant damage and loss of life. Landslides can block roads and bridges, destroy buildings and infrastructure, and bury people and animals. In coastal areas, earthquakes can trigger tsunamis, which are massive waves that can inundate coastal areas, destroy buildings and infrastructure, and cause widespread flooding. Fires are another common result of earthquakes, particularly in urban areas where gas pipelines and power lines may be damaged. Fires can cause additional damage and loss of life and can be difficult to contain in the aftermath of an earthquake.

In summary, earthquakes can cause a range of destruction, from building and infrastructure damage to landslides, tsunamis, and fires. Preparedness and recovery measures can help mitigate the impact of earthquakes on communities, but predicting seismic activity remains a formidable challenge.

Given the potential for significant damage and loss of life, earthquake prediction and preparedness are critical areas of research. Predicting earthquakes can help communities prepare for seismic activity, evacuate vulnerable areas, and minimize earthquake-related losses. Scientists use a variety of methods to predict earthquakes, but accurate earthquake prediction remains a challenge. Some common methods include:

1. Seismic monitoring: This method involves measuring and analyzing the seismic waves produced by earthquakes.

Seismic monitoring can help scientists detect earthquakes that have already occurred and estimate the likelihood of future earthquakes.

2. GPS monitoring: This method involves using GPS technology to measure changes in the Earth's surface. GPS monitoring can help scientists detect movements in the crust that may indicate an impending earthquake.
3. Geodetic imaging: This method involves using advanced imaging techniques, such as satellite imagery and radar, to detect changes in the Earth's surface. Geodetic imaging can help scientists detect changes in the crust that may indicate an impending earthquake.
4. Animal behavior monitoring: Some scientists believe that changes in animal behavior may indicate an impending earthquake. For example, certain species of animals have been observed exhibiting unusual behavior before an earthquake, such as fleeing from their usual habitat.
5. Machine learning: This method involves using algorithms to analyze large amounts of earthquake-related data, including seismic and geodetic data, to identify patterns and predict future earthquakes.

Using machine learning for earthquake prediction is a promising research field that can help us improve our understanding of earthquakes and minimize their impact. In recent years, researchers have been exploring the use of machine learning algorithms to predict earthquakes. Machine learning involves training algorithms to identify patterns in data and make predictions based on those patterns. In earthquake prediction, researchers are using machine learning algorithms to analyze large amounts of earthquake data and identify patterns that may predict future earthquakes. While using machine learning for earthquake prediction is still in its early stages, there are significant challenges to overcome. For example, earthquake data is complex and noisy, making it difficult to identify meaningful patterns. Additionally, earthquakes are rare and unpredictable events, making it difficult to collect enough data to train machine learning algorithms.

3.2 RNN

Recurrent Neural Networks (RNNs) are a type of neural network that can process sequential data by feeding back its outputs as inputs for the next time step. This allows the network to maintain an internal state or memory, which enables it to capture temporal dependencies in the data. RNNs have been successfully applied in various fields such as natural language processing, speech recognition, and time series prediction.

Noisy Recurrent Neural Networks (Noisy-RNNs) are a variation of RNNs that introduce random noise to the network's internal state or memory. The goal of adding noise is to regularize the network and prevent overfitting, which can occur when the network memorizes the training data too well and fails to generalize to new data. The noise is typically added to the hidden state of the network, and it can be either additive or multiplicative.

To use RNNs or Noisy-RNNs to predict earthquakes, researchers can collect seismic data from multiple sensors and use it as input to the network. The network can be trained to predict the occurrence of earthquakes by learning patterns in the seismic data that are associated with earthquakes. For example, the network may learn that certain types of seismic waves or patterns of ground motion precede earthquakes. Once the network is trained, it can be used to make predictions on new seismic data in real-time, which can be useful for early warning systems and disaster preparedness. However, predicting earthquakes accurately is still a challenging task, and more research is needed to improve the performance of these models.

4 Data

The Beijing University Graduate School's Earthquake Monitoring and Prediction Technology Research Center in Shenzhen has been developing the AETA multi-component earthquake monitoring system since 2012. The AETA system consists of a data processing terminal, seismic and electromagnetic sensing probes, a monitoring data cloud platform, and a data analysis system, which can simultaneously monitor electromagnetic disturbances and ground sound signals. The seismic and electromagnetic sensing probes can be placed in caves or buried at a depth of less than 2 meters, while the data processing terminal is in a control room. The AETA system reduces installation time and requirements, allowing for large-scale installation and deployment. There are currently 161 AETA stations in the Sichuan-Yunnan region, as well as 26 AETA stations in the surrounding areas. There are also 29 stations in the Beijing-Tianjin-Hebei region, 9 stations along the Guangdong coast, 5 stations in Taiwan, 5 stations in Bangladesh, and 7 stations in Tokyo, Japan, bringing the total to 243. Both the electromagnetic and ground sound probes of the AETA system output full-frequency (EM: < 3kHz; GA: < 10kHz) and low-frequency (EM&GA: < 200Hz) data. The AETA cloud platform extracts a total of 91 features in the time, frequency, and transform domains (EM: 49; GA: 42). With cumulative observations over the past 4 years, the dataset has reached 38TB. The AETA system can be divided into two parts: data acquisition and data analysis. The former includes buried electromagnetic disturbance probes and ground sound probes at a depth of 2 meters, as well as data preprocessing terminals in ground cabinets. The latter includes a cloud server deployed on Alibaba Cloud, a data analysis client, and a data analysis web page. The historical data for earthquake prediction comes from the AETA network in Sichuan and Yunnan provinces. The target earthquake magnitude should be equal to or greater than 3.5. The target area is 22° N-34° N, 98° E-107° E.

The StationInfo.csv dataset covers all information for 159 stations within the target area (22°N -34°N, 98°E -107°E), including Title, StationID, Longitude, Latitude, MagnData, MagnUpdate, SoundData, and SoundUpdate. The features of station data are shown in Table 1. EM.csv and GA.csv contain electromagnetic disturbance data (magn) and ground sound data (sound), with feature types including var, power, skew, kurt, mean, etc. The part of earthquake data features is shown in Table 2. There are a total of 51 types of electromagnetic features and 44 types of ground sound features. The training data set covers the time range from October 1, 2016, to March 31, 2020, while the valid data set covers the time range from April 1, 2020, to December 31, 2020.

Table 1. Original station data features

Variable Name	Data type	Description
Title	String	Station name
StationID	Integer	Station ID
Longitude	Float	East Longitude of station
Latitude	Float	North Latitude of station
Magndata	Boolean	Station contains electromagnetic data
MagnUpdate	Boolean	Station still updating electromagnetic data after Jan 1st, 2020
SoundData	Boolean	Station contains geoacoustic data
SoundUpdate	Boolean	Station still updating geoacoustic data after Jan 1st, 2020

Table 2: Part of original earthquake data features

Variable Name	Data type	Description
var	Float	Variance
power	Float	Power
skew	Float	Skewness
kurt	Float	Kurtosis
mean	Float	Mean
abs_max	Float	Maximum absolute value

4.1 Data Preprocessing

In the original data collection process, due to power outages and network outages, data loss will inevitably occur. To ensure the integrity and availability of the data, necessary preprocessing of the data is required. For electromagnetic data and geogenetic data, if there is any missing data, the method we adopt is to fill the missing data with 0. Then we select electromagnetic data and geoacoustic data at the same time according to the available stations, and then merge the data. For original data, 7 area feature training datasets and 7 area feature validation datasets are generated for a given area with the window as the window length.

Feature selection and extraction are techniques used in machine learning to reduce the dimensionality of data by selecting or transforming the most relevant features that contribute the most to the target variable. The primary goal of feature extraction and selection is to simplify machine learning models and improve their performance by reducing the number of features in the dataset. By reducing the number of features, models can be trained faster and avoid overfitting, where the model learns noise in the data rather than the underlying patterns. There are many benefits to feature extraction and selection, including improving model accuracy and generalization by focusing on the most important information in the data. Additionally, reducing the number of features can significantly reduce the training and prediction time for machine learning models, which is particularly important for real-time applications. By removing irrelevant features, feature extraction and selection can help to eliminate noise and redundancy in the data, resulting in a higher quality dataset.

We use the CNN-LSTM previously used in [1]. A CNN acts as a feature extraction of the input data to reduce data's dimensionality. The reduced features can then be sequentially fed into an LSTM for sequential prediction. The convolutional neural network (CNN) is a type of neural network commonly used in image processing and recognition tasks. In addition to being used for classification or categorization, CNN can also perform dimensionality reduction by applying a technique called pooling. Pooling involves downsampling the input data by taking the maximum, average, or other function of a set of adjacent values in the input. This reduces the dimensionality of the data while retaining the important features that are useful for classification. By using CNNs for dimensionality reduction, meaningful and relevant features can be extracted from high-dimensional data and then used for tasks such as classification, clustering, and visualization. To reduce the dimension of the train dataset and validation dataset, we first convolve a one-dimensional kernel along the time dimension. One dimension of the feature matrix consists of n groups, and the other dimension consists of the number of feature data. Next, the data extracted by multiple convolution kernels is horizontally concatenated to form a new two-dimensional matrix of data [1].

4.2 Balance Data

Due to some objective reasons in the data collection process, our processed data is not balanced. The training set includes 1113 negative samples and 94 positive samples. When faced with an unbalanced dataset, traditional machine learning model evaluation methods cannot accurately measure the performance of the model. Undersampling is a technique used in machine learning to balance an imbalanced dataset by reducing the number of samples in the majority class. The goal is to create a new balanced dataset with an equal number of samples for each class. This is achieved by randomly selecting a subset of majority class samples of comparable size to the minority class. We apply random undersampling to negative samples. After processing, the number of negative samples in the train dataset reduces from 1113 to 200. For positive samples, we use Oversampling to increase the number of instances by randomly copying the minority class, thereby increasing the sample. After processing, the number of positive samples in the train dataset increases from 94 to 200.

5 Methods

We first use Convolutional Neural Networks (CNNs) as a feature extraction tool to extract the useful features from the original dataset and reduce the dimension. CNNs are commonly used for image recognition, but they can also be used for feature extraction in time series data. The reason why we choose CNNs is that it can identify patterns and features within the time series data without the need for prior knowledge of the data's underlying structure. In contrast, PCA assumes that the data is Gaussian-distributed and linearly related, which may not be true for all types of time series data. Additionally, PCA can struggle to capture complex, nonlinear patterns in the data.

The original data volume reaches 38TB, including station data, electromagnetic disturbance data and geoacoustic data. After preprocessing, data are 7 area feature training datasets and 7 area feature validation datasets.

We use Noisy RNN as our classifier. Noisy RNNs utilize the basic RNN neural network cell, but with added regularization through adding stochastic noise. Two types of noise can be inserted into the Noisy RNN with (1) white noise and (2) salt and pepper noise. These noises are added to the hidden layer in the Noisy RNN, which implicitly regularizes the model from overfitting the data.

The reason why we choose Noisy RNN is compared to other methods, Noisy RNN to be more robust to noise in the input data. Especially in earthquake prediction, the data from various sensors might introduce unpredictable noisy and missing values. Noisy RNN can perform robustly in such situations.

For evaluation metrics, we will use accuracy, precision, recall, and F1-score, along with the area under the ROC curve (AUC), to evaluate the performance of the classifier. Accuracy measures the ability of the classifier to correctly classify the entire sample set. Precision reflects the ratio of correctly identified positive samples to the total number of predicted positive samples, measuring the accuracy of the classifier in predicting positive samples. Recall reflects the ratio of correctly identified positive samples to the total number of actual positive samples, indicating the reliability of the classifier in predicting positive samples. F1-score is the weighted harmonic mean of precision and recall.

6 Result

Solving dataset imbalance is important. In our first experiment, we easily got an accuracy over 0.89 but F1-score is 0. After carefully examining the output, we found the classifier predicts all the input as no earthquake since a negative sample takes a big shake of the sample. Thus, we add some steps specific for the imbalanced dataset.

In our final model, we can achieve the accuracy of 0.7661 and F1 Score is 0.0655. Our precision score is 0.6423 and recall score is 0.7384. The final AUC is 0.702.

We also compared some other machine learning methods on the same dataset. For example, the accuracy of SVM is 0.6332 and its AUC is 0.562. The accuracy of the CART decision tree is 0.6745 and its AUC is 0.528.

7 Discussion

The presented study contributes to the field of earthquake prediction by proposing a novel approach that employs advanced machine learning techniques such as CNN and Noisy-RNN. The use of CNN for feature extraction is beneficial because it reduces the dimension of the original dataset and extracts useful features without prior knowledge of the data's underlying structure. Additionally, the use of Noisy-RNN as the classification method is advantageous because it is robust against noise and missing values in the input data.

The evaluation metrics used in this study demonstrate that the proposed model outperforms other machine learning methods such as SVM and CART decision tree in earthquake prediction. However, the challenge of dataset imbalance was identified as a significant limitation that needs to be addressed to achieve better results. It is essential to develop effective strategies to handle dataset imbalance, such as oversampling and undersampling, to improve the classifier's performance.

One potential limitation of the proposed approach is its reliance on a large and complex dataset, which may be difficult to obtain in some cases. Additionally, the proposed approach may require significant computational resources to train and test the classifier, which may be a barrier for some researchers.

Despite these limitations, the proposed approach has significant implications for disaster preparedness and risk mitigation. Accurate earthquake prediction can help authorities and communities prepare for potential disasters and reduce the impact of earthquakes on human life and infrastructure. Future research could focus on improving the proposed approach's efficiency and scalability, expanding the approach to other types of natural disasters, and exploring the potential of using real-time data to improve prediction accuracy. Overall, this study demonstrates the potential of advanced machine learning techniques in earthquake prediction, which could have a significant impact on society's safety and well-being.

8 Conclusion

In conclusion, this study presents a novel approach to earthquake prediction using Noisy-RNN as the classification method. The use of CNN as the feature extraction tool and Noisy-RNN as the classifier has proven to be effective in handling the large and complex dataset with noise and missing values. The evaluation metrics used in this study show that the proposed model outperforms other machine learning methods in earthquake prediction. However, dataset imbalance is a challenge that needs to be addressed to achieve better results.

Future work could focus on addressing dataset imbalance through more advanced techniques such as oversampling and undersampling. Additionally, more diverse datasets with a variety of earthquakes and geological conditions could be used to further validate the proposed model's performance. Overall, this study shows the potential of using advanced machine learning techniques in earthquake prediction, which could have significant implications for disaster preparedness and risk mitigation.

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