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Attention Based Time Series Analysis for Earthquake Prediction

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Abstract

Term effects on people's health, mental well-being, and economic well-being, are among nature's most damaging and unpredictable threats. More than 1100 devastating earthquakes have occurred in the last century, resulting in the deaths of over 1.5 million people around the world. Most seismic vulnerability assessments in India are conducted at the municipal or state level, and they are based on traditional methods. Delhi, the northeastern section of India, and much of Gujarat, as well as the West Bengal plain, are particularly vulnerable to earthquakes. As ML has advanced fast in recent years, it has the potential to significantly transform and increase the role of data science across a wide range of academic disciplines. Complex issues, computing efficiency, propagation and treatment of uncertainty, and ease of decision-making are some of the advantages of ML over traditional techniques. In addition, improvements in machine learning (ML) have had a substantial impact on a wide range of scientific and engineering domains, including material science, bioengineering, construction management and transportation engineering. Support Vector Regressor and LSTM model is used to evaluate earthquake vulnerability in this study. Mean Absolute error below 3 percent is achieved.

Keywords: Earthquake prediction, Machine learning, Time series analysis, Regression Analysis, LSTM, Support Vector Regressor.

Introduction

A tectonic plate movement or a shift in the earth's crust can cause an earthquake, which is a natural calamity. An enormous amount of energy is released as a result of this rapid movement, resulting in seismic waves. The earthquake's impact on the earth's surface resulted in damage to the people who live there. India is one of the most earthquake-prone countries in the world because of the ongoing convergence of the Indian and Eurasian plates. Figure 1 shows earthquake vulnerable zones in India, where zone 5 represents most vulnerable. India has been hit by numerous devastating earthquakes over the years , including the 1803 A.D. Kangra earthquake, the 1934 Nepal-India earthquake, the 1950 Upper Assam earthquake, and the 2005 Muzaffarabad earthquake along the Himalayan region[2.3] . Nearly 20,00 died in the Kangra earthquake of 1905 and a significant amount of property damage and rehabilitation costs were incurred in the Bihar-Nepal border earthquake of 1934, between 10,000 and 12,000 people were killed, around 5,000 were killed in the Upper Assam earthquake of 1950, and approximately 87,000 people were killed in the Kashmir earthquake of 2005 [4]. The 2001 Bhuj earthquake in Gujrat, India, caused extensive property damage and 20,000 deaths around Bhuj, Gujrat, India, in addition to the Himalayan earthquakes[5].

The Himalayan arc is known to be capable of causing massive earthquakes. **The Indian subcontinent is prone to devastating earthquakes that affect millions of people . A major earthquake in the Himalayan and Indo-Gangetic Plain region, with its dense population and rapid urbanization, would be a catastrophic event [6].** Many remote and volcanic areas already have earthquake warning systems in place, which could lead to an increase in the number of people expecting to survive an earthquake. Figure 1.2 depicts a system for early warning of earthquakes. System of accelerometers, seismometers, communication, computers and alarms, an earthquake warning system or earthquake early warning system is designed to notify adjoining regions of a substantial earthquake while it is in progress.

Early warning systems for earthquakes do not foretell earthquakes. As an alternative, they monitor for ground motion and send out alerts as soon as an earthquake begins, giving people critical seconds to prepare[7]. The timing, location, and magnitude of an upcoming earthquake can be accurately predicted by identifying distinct precursors[8]. The "foreshock–mainshock–aftershock" sequence is well-established as a possible prelude to earthquakes and a possible follow-up of aftershocks . Forecasting well in advance of an earthquake may be possible if faults slip in a completely deterministic manner; forecasting just prior to failure may be possible, but not for very long. It's still a long way off from being able to predict and forecast earthquakes with any degree of accuracy, but recent research on laboratory earthquakes provides some hope.

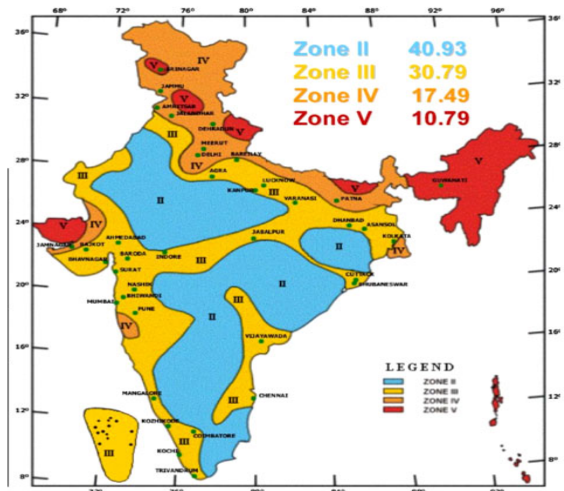

Figure 1 : Seismic zones in India

The use of machine learning (ML) in geoscience has grown significantly over the past two decades. A confluence of new ML algorithms, fast and inexpensive graphical processing units and tensor processing units, and massive, often continuous datasets has driven this revolution in data-driven analysis. This rapid expansion has seen the application of existing and new ML tools to a wide range of geoscientific problems[9-10] , including seismic wave detection and phase identification and location, geological formation identification, earthquake early warning, volcano monitoring, denoising Interferometric Synthetic Aperture Radar (InSAR), tomographic imaging, reservoir characterization, and more. The use of historical seismic data has helped improve earthquake prediction. Machine learning (ML) and Artificial Intelligence (AI) are the most promising techniques. ML algorithms are used to analyses historical seismic data and classify the sequence as severe or normal. Conventional methods are difficult to use to identify low Signal to Noise Ratio (SNR) seismic events. **Autocorrelation is a benchmark technique that requires O(N2) time.** Even weeks of data cannot be autocorrelated with a standard computer over long periods of time.

The objective of this research is to develop a earthquake prediction system using deep learning. The rest of the paper is organized as follows Section II summarizes the literature review in microgrid fault detection, the implementation is discussed in section III. Experimental results are analyzed in section IV. Finally section V concludes the research and mentions future scope.

Literature Review

Predictions for earthquakes are discussed in this section in depth. Because earthquakes are a very unpredictable phenomena, it is unknown whether there exists a model that can reliably predict the time, location, and magnitude of an earthquake. Numerous investigations have been undertaken by researchers in this discipline over the years. Researchers have attempted to tackle this issue from a variety of angles in order to identify a potential answer. This section will discuss several of these studies that are pertinent and beneficial to this research.

There are two distinct techniques to earthquake prediction: precursor-based and trend-based. **Precursors are events or indications that occur before to the occurrence of an earthquake, such as radon gas emissions and aberrant animal behavior.** Kuyuk et al. [11] provide an excellent example of precursor-based prediction. They describe how they trained a Long Short Term Memory (LSTM) to assess data from Earthquake Early Warning systems in order to detect earthquakes before the seismic waves reach the heart of a city or a highly populated area in this paper. This has the potential to save many lives, as being aware of an earthquake even a few minutes sooner improves evacuation tactics dramatically .

Trend-based methods use real-world data (e.g., seismicity, prior earthquakes, etc.) to discover trends that can be used to predict earthquakes. Finding studies that are comparable to this one will be helpful in this study's trend-based prediction. Asim et al. [12] used historical seismic data to estimate the magnitude of earthquakes in the Hindukush region. Pattern recognition neural network, recurrent neural network (LSTM), random forest with 50 trees and linear programming boost ensemble were all used to learn from the data. Using a pattern recognition neural network, the researchers were able to forecast earthquakes with an accuracy of 66%. Trend based earthquake prediction system has remained primary research focus as data acquisition and relationship mapping is less complex as compared to precursor-based systems. Regression Analysis, Decision trees and Neural networks are the major techniques used in this domain. Previously published research work related to these techniques are discussed in the following section

According to Li and co-workers [14], the arrival time of primary (P) and secondary (S) waves were predicted using an ML approach. There were 16 seismological stations where they gathered their data. SAC files were used to store the data.

Mallouhy et al. [15] in order to determine whether an earthquake occurrence may be classed as major or small. This research explains how different machine learning methods can be applied to earthquake data in order to better understand how they work. When compared to other models, the Random Forest and K closest neighbor algorithm produced the greatest results.

H. Adeli and A. Panakkat [16] approach earthquake prediction as a classification problem, with the output classes being the magnitude ranges of the largest seismic events within a predefined time window (for example, 1 month). A month in the future, using the proposed methods, an earthquake in a predefined region is expected to have a magnitude greater than or equal to (within 0.5).

Another ANN-based earthquake prediction method was proposed by J. Reyes et al.[17]. An earthquake larger than a predetermined threshold magnitude is expected to occur within five days, and a seismic event of a predetermined magnitude range is expected to occur within that time frame. Gutenberg-law Richter's provided the b-value for the proposed predictor. When the probability of an earthquake exceeded a predetermined threshold, the prototype predicted an earthquake (the thresholds were adjusted to reduce the number of false alarms).

Earthquake forecasting using ANNs was the focus of an experiment conducted by E. M. Moustra and et al [18]. There are two key areas of study that the paper focuses on in particular. The size and time lag of the following seismic event were both predicted using time series earthquake magnitude data and so-called Seismic Electric Signals (SES). In the beginning, we employed a feed-forward backpropagation neural network. An input file contained the greatest magnitude for each day. For the model's training and evaluation, it was used a Greek earthquake catalogue and an MAE-derived accuracy rate was used to measure its performance. Only "outliers" had an accuracy rating of 52.81 percent, which is lower than the 80.55 percent for all events (earthquakes of magnitude greater than 5.2.

Proposed Methodology

The goal of this study is to develop a framework for the analysis of time series data to predict earthquakes. For the same purpose, time series analysis and machine learning are employed. The entire study can be broken down into five major phases, as shown in Fig. 2, namely the collection of databases, the normalization of databases, the training, the testing, and the validation. Following sections describe each phase.

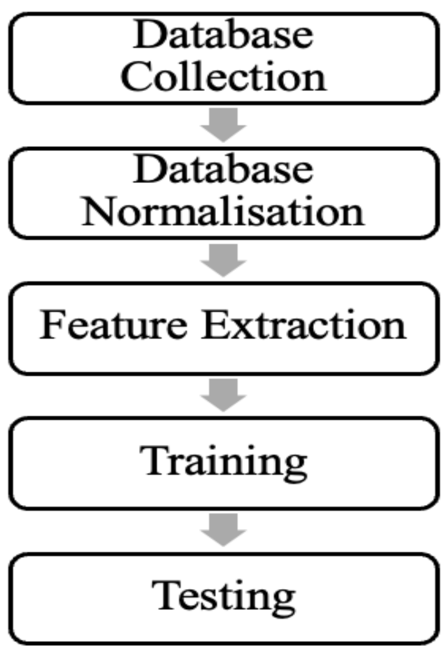

Figure 2: Block diagram of process flow

3.1 collection :

The Kaggle LANL competition provided the data for this study. Seismic signals will be used to forecast the timing of laboratory earthquakes as part of this competition. It is based on a well-known earthquake physics experiment set up.

Predicting the time until the next laboratory earthquake (time to failure) is done by using the acoustic data input signal

The input variable is acoustic data signals. Figure 3 shows the acoustic signal trend. Effort to failure is the metric to be measured. There's a maximum value of 16 seconds, and a minimum close to zero, for the target variable (1e-5). The target variable is shown in Fig. 4.3.

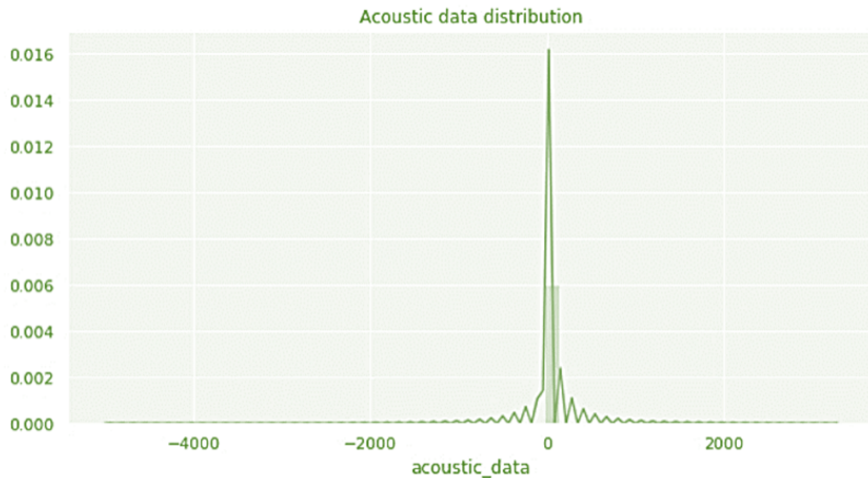

Figure 2: Acoustic signal of laboratory earthquake

3.2 Pre processing and normalization

Normalizing data refers to the process of making data better in order to get better results. In this study, null values were examined first to see if they contained any garbage. These entries have been deleted from the database. The pre-processed database is normalized using the equalization histogram. It is now possible to extract features and perform machine learning on them.

The time series data is broken down into smaller sequences so that it can be analysed more effectively. After that, the intervals are subjected to the floor function. There's a NumPy. Floor function that returns the square root of an array's elements. An integer that is larger than x is called the floor of a scalar. This is followed by a split of the data into a training and a testing set. We used 70% of the data for training and 30% for testing and validation in this study, according to the standard notation.

3.3 Feature Extraction

When raw data sets are transformed into numerical features that can be processed, the original information is preserved. In comparison to applying machine learning directly to raw data, this method provides better results Machine learning algorithms are more efficient when they are able to use features extracted from a signal's most distinguishing characteristics. Because of the high data rate and information redundancy, training machine learning or deep learning directly with raw signals often yields poor results. In this study, we drew on the following extracted features:

- Mean magnitude/Avaergae (Mmean): It represents the mean of n events, and in this context it refers to magnitude of earthquake.
- Standard deviation (σb): Standard deviation is a measure of how much variation there is in a set of values. The mean (also known as the expected value) of a set has a low standard deviation, whereas the values in a set with a high standard deviation are dispersed over a wider range.
- Maximum Value : It refers to the maximum value or peak value of the interval.
- Minimum Value : It denotes the minimum value obtained in the interval.
- Median : The median in statistics and probability theory is the value that divides a data sample, a population, or a probability distribution in half in the middle.
- Kurtosis : A real-valued random variable's kurtosis is a measure of the probability distribution's "tailedness" in probability theory and statistics. A probability distribution's shape is described by kurtosis, which can be quantified in various ways for theoretical distributions as well as from a sample from the population. Different kurtosis measures may be interpreted differently.

• Skew The skewness of a real-valued random variable's probability distribution is a measure of its asymmetry with respect to the mean. An undefined value or a negative or zero value can be used to describe a skewed distribution.

• Rolling mean : Analysis of data points (rolling average or running average) can be done by creating multiple subsets of the full data set, and a moving average is a calculation that does this. The training data is typically grouped every 150,000 rows, and statistics are calculated for each chunk.

• In order to accurately represent each time interval in a time series, additional features like the minimum and maximum values, the hilberts mean, and so on are extracted. A dataframe is used to store the extracted information.

The next step is design and training of Machine learning models. Support vector Regressor and LSTM models are used in this research

Result and Discussion

On a 64-bit Windows 10 machine with a 1TB hard drive and 8 GB of RAM, the algorithm for detecting disease in leaf images is running in Python 3.9. TensorFlow and Sklearn python libraries are both used in this study.

The target variable is time to failure. The expected outcome of this research is prediction of time to failure with maximum efficiency. Figure 3 shows the actual and predicted values of time to failure obtained with Support vector regression. The trend of actual and predicted values observed in LSTM is shown in Figure 4

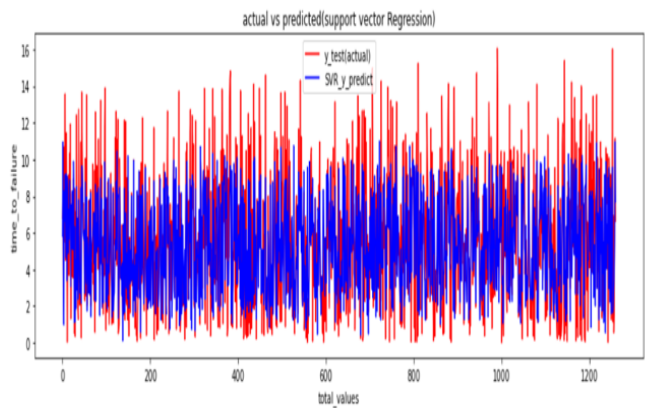

Figure 3: Actual vs predicted value in SVR.

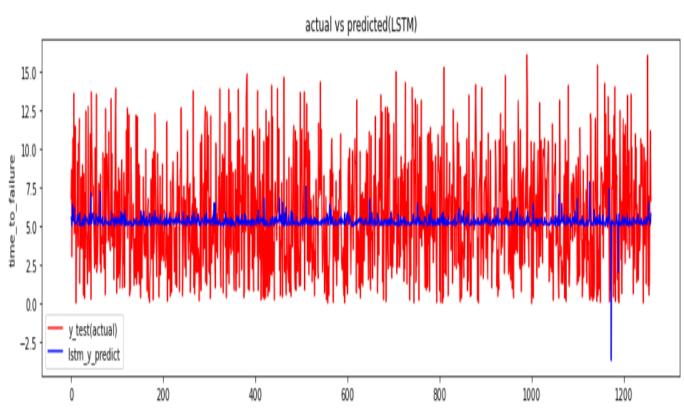

Figure 4: Actual vs predicted value in LSTM

SVR outperforms LSTM in terms of performance. The mean absolute error is a critical performance metric in this study. A statistical measure known as the mean absolute error (MAE) is a comparison of errors between two observations that express the same phenomenon. There are many examples of Y versus X, including comparisons of predicted versus observed, subsequent versus initial time, and one measurement technique versus another. The formula for MAE is: Mean Absolute Error can be calculated as:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \qquad (1)$$

where $\hat{y}_i$ is predicted value, y_i is actual value and N is the total number of datasets.

Table 1

	SVR	LSTM
Mean Absolute error	**2.07**	**3.08**

Conclusion

In this research an earthquake prediction system is demonstrated using time series analysis. Extensive literature review reveals that neural networks are the most preferred technique for this approach. Recurrent Neural Networks are particularly suited for time series analysis but suffer from the problem of vanishing and exploding gradient. Attention based mechanism are a possible solution. In this research two machine learning techniques namely Support Vector Regressors and Long Short Term Memory neural network is applied on lab generated seismic data. Appropriate feature extraction techniques were applied including kurtosis and skewness extraction. Both the models show significant performance with mean absolute error less than 4 percent.

The proposed research has ample scope for future work. The performance of the proposed LSTM network can be enhanced by using meta heuristic optimization. The proposed research can be tested on different real life datasets to gain a more efficient perspective on the efficiency of the model. A hybrid precursor and trend based approach can be presented

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