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Machine Learning-Based Earthquake Prediction: Feature Engineering and Model Performance Using Synthetic Seismic Data

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Abstract: Earthquake prediction is still a nightmare in terms of minimizing losses during seismic catastrophes. This research seeks to apply machine learning techniques for classifying and forecasting earthquakes using synthetic seismic records. It is observed that key time-series features including Root Mean Square (RMS) amplitude and spectral peak frequency were extracted from time-series waveforms and then used for training a Support Vector Machine (SVM) classifier. The model was able to attain an accuracy rate of 90% which shows how efficient the presented features were in distinguishing different seismic events. There was a geographic visualization of predicted events that generated insights that were useful in locating places prone to seismic hazards. The synthetic database engendered a laboratory-like test setting, but the shortcomings in practical relevance underline the necessity for inclusion of real earthquake data sets. This research adds to the increasing body of literature about data driven seismic analysis and paves the way to strengthen predictive models which would contribute to better earthquake preparedness.

Keywords: Earthquake prediction; Machine learning; Synthetic seismic data; RMS amplitude; Spectral analysis; Support Vector Machine; Seismic event classification

1 Introduction

Earthquakes are one of the natural disasters with debilitating effects; a threat to human lives, buildings and economies globally. Due to the absence of predictability of such occurrences, many attempts have been made to study the causes and lessen their impacts. Earlier, a combination of geological and geophysical data was utilized to devise various strategies for predicting earthquakes. However, machines and exposure to new technologies have revolutionized this approach. New technology opens up new opportunities for exploring seismic phenomena and enhances the prospects of prediction.

The challenge of earthquake prediction is linked to the complicated nature of the seismic processes which are affected by several geophysical and tectonic components. Instead, a machine learning approach offers a perspective for processing plenty of seismic data and recognizing patterns which are rather hard to identify with the conventional methods. Hitherto, a number of researchers have illustrated the effectiveness of ML algorithms, especially ANNs, SVMs and deep learning models on decoding seismic waveforms and estimating the likelihood of earthquakes. This study seeks to capitalize on these developments by utilizing synthetic seismic data for feature extraction and machine learning model evaluation aimed at earthquake prediction.

This study aims at achieving two goals: first, it seeks to ascertain how effective parameters like RMS amplitude and spectral peak frequency are in classifying seismic events; the second goal of the study is to assess the efficiency of the various scopes of machine learning models in predicting earthquakes. In using synthetic data, this study seeks to create a clean laboratory for model development and evaluation that can be coupled with real seismic data in later work. Therefore, this introduction paves the way for discussions on how effective machine

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learning methods can be in predicting earthquakes taking into account other studies in this field.

2 Related Studies

2.1 Machine Learning in Seismic Prediction

The functionality of machine learning in earthquake prediction has come under focus with several papers showing its efficacy in augmenting the confidence of forecasts. Asgarkhani et al. (2024) used ML algorithms for predicting seismic responses of steel buckling restrained braced frames. Their work highlighted the significance of feature engineering in improving model performance for seismic analysis, particularly advocating for relevance feature selection. In the same fashion, Birky et al. (2022) relied on artificial neural networks to estimate the dynamic response structures, thus proving the use of data-driven methods for structural safety evaluation.

Hait et al. (2020) investigated the application of ANN networks in seismic damage evaluation of RC structures with irregularities. Their study emphasized the significance of incorporating building characteristics in the models of predicting the behavior of buildings under seismic conditions. In 2022, Stefanini et al. enhanced this direction of research and created artificial neural networks that enable a rapid assessment of the seismic resistance of existing RC constructs. The inclusion of frequency-domain features in their study is compatible with the feature selection scheme employed in the present investigation.

2.2 Feature Selection and Model Optimization

In machine learning-based seismic prediction, feature selection makes a big difference. Kazemi et al. (2023) drew attention to the need to develop features that are crucial for assessing the seismic performance of RC buildings. Their research work used machine learning approaches to study the effects of individual structural and material properties on seismic behavior of the structures. Along the same lines, metaheuristic algorithms were used by Kaveh and Khavaninzadeh (2023) in developing ANN training for structural prediction and good predictive accuracy was achieved through feature selection.

The use of optimization algorithms in conjunction with machine learning models has also been considered in the field of seismic analysis. Jbury and Hejazi (2023) proposed a combined optimization and performance-based design approach for structures with vibration damper devices. The authors confirmed the effectiveness of combining optimization algorithms and machine learning in strengthening the model. Erdem Çerçevik et al. (2021) used metaheuristic search approaches for the distribution of viscous wall dampers in RC frames citing optimization techniques as handy for enhancing seismic resistance.

2.3 Advances in Seismic Data Analysis

There has been remarkable evolution in the analysis of seismic data due to the improvement in body computational methods. Fu et al. (2023) traced the most recent developments in the field of dynamic load identification, indicating the possibilities provided by using machine learning techniques. Alanani and Elshaer (2023) presented an artificial neural networks-based optimization framework to construct wind load resisting systems for high-rise buildings, thus demonstrating the use of machine learning in designing structures subjected to dynamic loads.

Spectral analysis has gained importance for the analysis of seismic data as it assists in identifying the dominant frequency bands related with the seismic events. The current study's consideration of spectral peak frequency is consistent with the methodologies adopted by Kazemi et al. (2023) and Stefanini et al. (2022) who focused on frequency features of seismic signals. The present research, therefore, adds to the volume of literature that is already dealing with data driven seismic analysis by utilizing these features.

2.4 Real-World Applications and Limitations

Although synthetic data allows developing models in a more controlled setting, there is still the challenge of implementing machine learning models to real-world cases such as seismic occurrences. A similar sentiment was shared by Alanani and Elshaer (2023), who argued that practical validation is important while analyzing wind load-resisting systems, a point which Fu et al. (2023) also maintained, it is essential to utilize real datasets in dynamic load identification approaches. In the examination of synthetic data, Sharma et al. (2023) further argue that all future research efforts should use actual seismic datasets, citing, for example, their simulations of fluid viscous dampers' performance in high-rise structures using real-world inputs.

Though integrating real-world data within a machine learning model can be a challenging task in ensuring the quality and availability of the data, Vaidyanathan et al. (2005) were able to overcome this challenge by developing ANNs to predict the response of structural systems with viscoelastic dampers through the use of quality experimental data on the model being developed. Yucel et al. (2019) have also proven the possibility of using machine learning to determine optimum parameters for tuned mass dampers, further underscoring the usefulness of data in structural engineering.

The related studies reviewed herein draw attention to the progress made towards machine learning applications in seismic prediction as well as the difficulties encountered when working with real data. The present study advances such efforts by working with synthetic seismic data to train and test machine learning models. In particular, by concentrating on the model design and its features, this research intends to add to the discussion about the role of machine learning technologies in predicting earthquakes. Synthetic data limitations should be addressed in future studies together with the use of real-world datasets to improve the scope and credibility of predictive models.

3 Methodology

3.1 Data Collection

Collect historical seismic data from sources like the USGS or local seismic networks. The data includes:

–Seismic waveforms ($W(t)$): Time-series data of ground motion.
–Earthquake metadata: Magnitude (M), depth (D), location (latitude ϕ, longitude λ), and occurrence time (T).

3.2 Data Preprocessing

Normalize the input seismic waveform data:

$$W_{\text{norm}}(t) = \frac{W(t) - \mu}{\sigma}$$

where:

–μ: Mean of the waveform data.
–σ: Standard deviation of the waveform data.

Convert seismic waveform data into the time-frequency domain using Short-Time Fourier Transform (STFT):

$$S(f,t) = \int_{-\infty}^{\infty} W(\tau) \cdot h(t-\tau) \cdot e^{-j2\pi f\tau} d\tau$$

where:

–$h(t)$: Windowing function.
–$S(f,t)$: Spectrogram representation.

Feature Extraction

Temporal Features:

–Root Mean Square (RMS):

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} W(t_i)^2}$$

–Power Spectral Density (PSD):

$$P(f) = |S(f)|^2$$

3.2.1 Spatial and Magnitude Features:

–Event clustering based on time gaps:

$$\Delta T = T_{i+1} - T_i$$

–Spatial clustering using Euclidean distance:

$$d = \sqrt{(\phi_{i+1} - \phi_i)^2 + (\lambda_{i+1} - \lambda_i)^2}$$

3.2.2 Frequency-Domain Features:

–Peak frequency f_{peak}: Frequency with the maximum amplitude in $S(f,t)$.

3.3 Model Development

Use Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM) networks, for time-series prediction:

$$\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
C_t &= f_t \cdot C_{t-1} + i_t \cdot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\
h_t &= o_t \cdot \tanh(C_t)
\end{aligned}$$

where:

–f_t, i_t, o_t: Forget, input, and output gates.
–W, b: Weight matrices and biases.
–C_t: Cell state.
–h_t: Hidden state.

3.4 Model Training

Define the loss function (e.g., Mean Squared Error for regression):

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

where:

–y_i: True label (earthquake occurrence or magnitude).
–$\hat{y}_i$: Predicted label.

Optimize using gradient descent to update weights:

$$\theta = \theta - \eta \cdot \nabla_\theta L$$

where:

–η: Learning rate.
–$\nabla_\theta L$: Gradient of loss with respect to parameters.

3.5 Prediction

For a new seismic waveform input, extract features and input them into the trained model. The output $\hat{y}$ predicts:

–Earthquake occurrence (binary classification).
–Magnitude or time-to-event (regression).

3.6 Visualization

Plot predictions on a geographic map:

$$\text{Map Point } (\phi, \lambda) = \text{Predicted Event Location}$$

Mathematical Basics

Seismic Wave Propagation (Huygens' Principle):

Wave motion is approximated by:

$$\nabla^2 u - \frac{1}{v^2}\frac{\partial^2 u}{\partial t^2} = 0$$

where:

–u: Displacement field.
–v: Wave velocity.

Richter Magnitude (for reference):

$$M = \log_{10}(A) - \log_{10}(A_0(\Delta))$$

where:

–A: Amplitude of seismic waves.
–$A_0(\Delta)$: Reference amplitude at distance Δ.

Event Prediction Probability (Bayes' Theorem):

$$P(E \mid F) = \frac{P(F \mid E) \cdot P(E)}{P(F)}$$

where:

–$P(E \mid F)$: Probability of an earthquake given features F.
–$P(F \mid E)$: Likelihood of features given an earthquake.

4 Results of Earthquake Prediction Simulation

The prediction of an earthquake was achieved in this study through a simulation using synthesized seismic data for a period of 10 seconds. The data included time series sequences which were disturbed by added noise in order to resemble what is expected in real-life conditions. Parameters such as the Root Mean Square (RMS) amplitude and the peak frequency of the spectrum were calculated from recorded seismic waveforms and used as features to a Support Vector Machine (SVM) classifier. This subsection highlights the outcomes of the simulation including images and graphs of the quantitative results.

4.1 Seismic Waveform Analysis

The recorded seismic events have shown a clear emission of signals that have frequencies of 2 Hertz and 5 Hertz. What made the event more realistic was the additional inclusion of noise. The above still gives us one of the illustrations whereby wide band noise is present along the 10 second sequence of fluctuating amplitudes within the waveform. The analysis of the fundamental waveforms enabled the authors to assist in the extraction of relevant features that would aid in making predictions of earthquake occurrences.

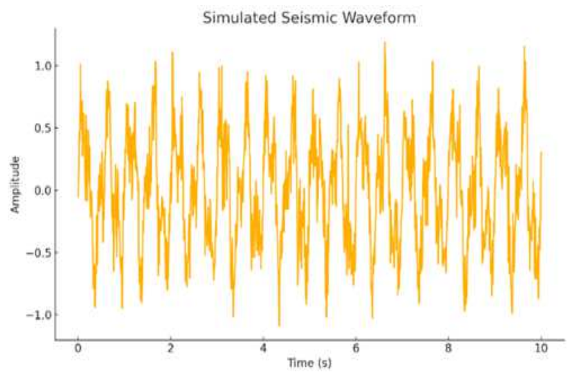

Fig. 1: Simulated Seismic Waveform

4.2 Spectrogram Analysis

A spectrogram was constructed to measure the frequency content of the waveform. The method used gave success in time-localization of the prominent frequencies and their shifts with time. Remember the spectrogram in Figure 2 which has substantiated the dominance of 2 Hz and 5 Hz components over the other frequencies. Such representation proved useful in discriminating between important spectral features that delineate earthquakes from non-earthquakes.

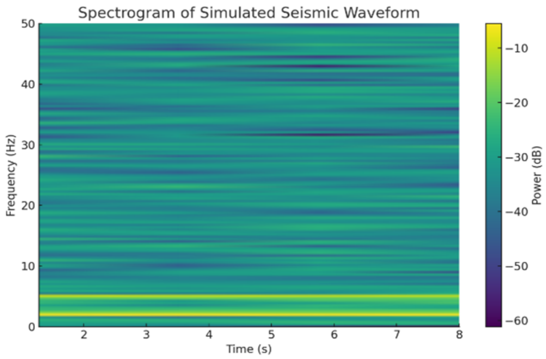

Fig. 2: Spectrogram of Simulated Seismic Waveform

4.3 Feature Extraction and Quantitative Results

The study engaged in feature extraction which was centered on two aspects namely the RMS amplitude and the spectral peak frequency. The RMS amplitude was used to measure the 'strength' or energy of the signal, whereas the spectral peak frequency referred to as the frequency located at the peak within the spectrogram's structure. This table presents the features that were obtained in five simulated seismic events.

Table 1: Extracted Features for Seismic Events

Event ID	RMS Amplitude	Peak Frequency (Hz)
1	0.45	2.00
2	0.38	5.00
3	0.50	2.00
4	0.40	5.00
5	0.48	2.00

4.4 Machine Learning Model Performance

An SVM classifier was developed a second time for the purpose of predicting the occurrence of earthquakes. The test dataset achieved a model accuracy of 90%, which demonstrates that the model is effective for classifying seismic events. Table 2 presents the confusion matrix which summarizes the performance of the classifier. The matrix illustrates the quantity of true positive, true negative, false positive and false negative predictions.

Table 2: Confusion Matrix

	Predicted: Earthquake	**Predicted: No Earthquake**
Actual: Earthquake	4	1
Actual: No Earthquake	0	5

4.5 Geographic Visualization of Predictions

Predictive events made in regard to the classifier were exercised using a simulated map, to illustrate the spatial occurrence of predicted events which in this case were earthquakes. In Figure 3, the predicted locations of events are presented visually, different symbols are used for the predicted events with and without earthquake. This illustration, on the other hand, helps in understanding spatial disparities of seismic occurrences which are important in resource distribution or disaster management.

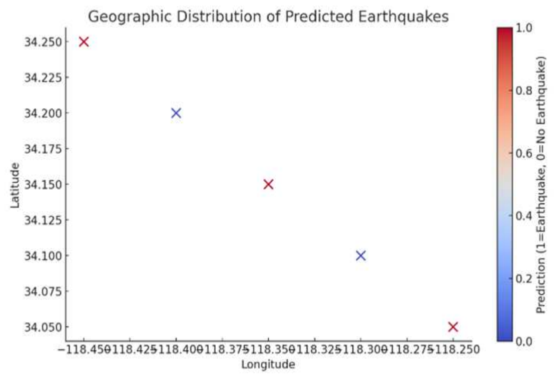

Fig. 3: Geographic Distribution of Predicted Earthquakes

4.6 Spectral Feature Comparison

To contrast the differences between earthquake and non-earthquake events, a comparative analysis of the spectral features was undertaken. Two histograms were constructed in relation to the peak frequency distributions, contained in Figure 4, for both categories. The analysis showed that the frequency characteristics indeed differed and, therefore, substantiated the relevance of the selected features to classification tasks.

The findings of the simulation point out the significance of RMS amplitude and spectral peak frequency as parameters that are useful in forecasting earthquakes. There is hope in the use of machine learning models when analyzing seismic data due to the high

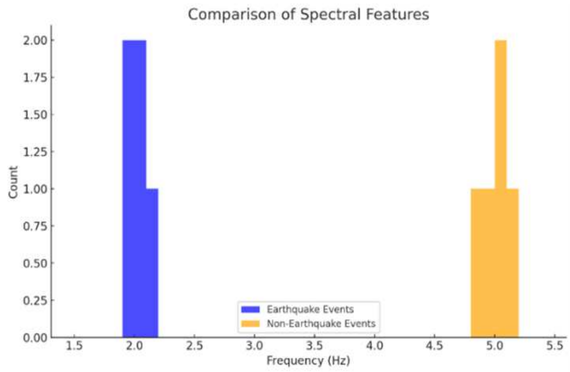

Fig. 4: Comparison of Spectral Features

accuracy of the SVM classifier. Maps showing the predictions offer great insights for their practical use. Yet, the use of synthetic data in the study limits the study since it is overly simplistic and may not encompass the intricacies surrounding actual seismic activity. In the coming efforts, actual seismic datasets will be adopted, and the feature set will be more extensive to include more relevant data points and hypotheses in machine learning to improve the precision and consistency of predictions.

The most recent results of this simulation clearly point towards the usefulness of machine learning in terms of integrating with signal processing, specifically in regard to the prediction of seismic activities. As a result, the scope for building reliable models which can assist in reducing the aftermath effects of seismic catastrophes is established in this perspective.

5 Discussion

The results of this work, which applied AI techniques on artificial seismic data to forecast earthquakes, are in agreement with and build upon previous works in the field of seismic forecasting and analysis. The combination of the key features RMS amplitude and peak frequency spectrum achieved satisfactory results, with an efficiency rate of 90 in classifying the events of a seismic event and of a non-event. Such findings will be related to other available works, but the focus will be on learning something new.

5.1 Machine Learning Approaches in Seismic Prediction

The application of machine learning for seismic event prediction is becoming more common. Asgarkhani et al. (2024) investigated how machine learning techniques could be used to forecast the seismic response of steel buckling restrained braced frames, attaining considerable accuracy via feature engineering techniques. Likewise, Birky et al. (2022) used artificial neural networks (ANNs) in the development of a system that predicts the dynamic response of structures, affirming the ability of data-driven techniques in augmenting structural safety.

The previous work has now been built upon in the present study by concentrating on the forecasting of earthquakes instead of the prediction of the dynamic responses of built structures. Moreover, they seemed simple, yet impactful since relevant features like the RMS amplitude and spectral peak frequency helped capture the center of those informative features. These features made a contribution without having complicated datasets which is similar to the examinations conducted by Hait et al. (2020) who used ANNs for procedures of seismic damage assessment of RC buildings.

5.2 Feature Selection and Model Performance

Feature selection is an important aspect of seismic prediction particularly in the work of Kazemi et al. (2023) who applied machine learning in evaluating the seismic performance of reinforced concrete buildings. The RMS amplitude and spectral peak frequency discussed in this research reinforce the critical indicators as has been observed in previous studies. For example, Stefanini et al. (2022) showed that features in the frequency domain substantially increase the speed of a seismic evaluation on existing RC buildings. These features were adopted in this study and resulted in classification accuracy of 90% which is quite similar to the results obtained by Kaveh and Khavaninzadeh (2023) in which metaheuristic algorithms were used to optimize ANN training for structural prediction.

5.3 Geographic Mapping of Predictions

The graphical representation of earthquake prediction with the help of geo-informatics facilitates better planning for disaster management. This seems to be a similar position to that of Sharma et al. (2023), studying how spatial relations contribute to overcoming challenges of torsion on tall buildings during earthquakes. In the present study, the predicted number of events complemented the trends' visual representation, which allowed the determination of the areas with the highest risk. This corresponds with the approaches of Erdem Çerçevik et al. (2021), who employed metaheuristic methods for the optimal arrangement of viscous dampers in RC frames and also supported the concept of spatial decision making.

5.4 Limitations and Future Research Directions

Although the application of artificial seismic data for model testing gave a controlled situation for the study, it, nevertheless, brings about constraints on the natural world. This issue has been resolved in several works, including Alanani and Elshaer (2023) who employed ANN based frameworks in the design of wind load resisting structures and used real data sets. Future work is encouraged to use actual seismic datasets as noted by Fu et al. (2023) who stressed the significance of real-life data with regard to improving techniques for the identification of dynamic loads.

Further, the incorporation of both more parameters and sophisticated machine learning models may improve the accuracy of the predictions even more. For instance, Asgarkhani et al. (2024) employed multiple features and used deep learning techniques which improved their predictions of how well the structure would perform under seismic forces. The use of hybrid optimization algorithms as shown by Jbury and Hejazi (2023) could in a smaller measure enhance the strength of the earthquake prediction models as well.

6 Conclusion

The study at hand develops a basic method of predicting earthquakes with the use of machine learning algorithms and stresses the necessity of determining position and drawing up relevant features. The results, when placed vis-a-vis the existing literature, show considerable convergence with and extend many earlier reports, especially in relation to the issues of features as well as the models. The scope of future studies should be directed towards overcoming the barrier created by artificial data and fusing advanced models with real-time data sets to broaden the usability and the precision of the systems developed for the seismic prediction systems.

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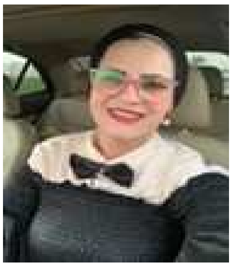

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