A Critical Review on Leveraging Artificial Intelligence for Seismic Risk Mitigation: A Machine Learning Approach

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Abstract. For decades, earthquake prediction has been a significant challenge in seismology. Especially in tectonically complex and densely populated regions, delivering accurate forecasts has become increasingly complicated. This is due to the nonlinear and multifarious nature of these seismic processes that traditional statistical and geophysical approaches struggle to deliver reliable insights. But in the recent years, advances in artificial intelligence (AI) and Machine Learning (ML) have opened new pathways for obtaining predictive insights from heterogenous datasets which include seismic catalogs, satellite imagery, and geodetic measurements. Machine learning techniques are increasingly being used in seismology, detecting hidden signals and patterns, as well as identifying features that could enhance our understanding of seismic phenomena. This paper evaluates earthquake prediction through the implementation of some of the leading ML models like – Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Extreme Gradient Boosting (XGBoost) in earthquake prediction tasks such as magnitude estimation, time to-event forecasting and epicenter localization. A substantial amount of effort has been put in to devise effective learning algorithms to predict earthquakes, but there has very little less development for standardized benchmarks to promote future progress in this field. For instance, hybrid architectures, such as CNN-SVM frameworks, top the benchmarks showing up to 98.5% accuracy in binary occurrence classification, as reported in recent studies. Additionally, the performances of these models were enumerated to identify the most accurate ones. Finally, the paper highlights the potential and limitations of current approaches, offering actionable insights for the development of earthquake forecasting systems.

Keywords: Earthquake prediction, Machine Learning (ML), Artificial Intelligence (AI), Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs)

1 Introduction

1.1 Background

An earthquake is a sudden release of energy within the Earth's lithosphere caused by tectonic forces, volcanic activity, or human activities (e.g., mining). This energy propagates as seismic waves, resulting in ground shaking and displacement. The hypocenter denotes the rupture's origin depth, while the epicenter is its surface projection. Conventional earthquake prediction methods, such as the seismic gap hypothesis [1-5] and statistical models like ETAS [6], face limitations due to their simple assumptions about fault mechanics and linear precursor relationships. These methods often fail to account for complex fault interactions [7], non-linear precursor signals (e.g. thermal anomalies, ionospheric disturbances) [8]. Sparse historical catalogs [9] and class imbalance [10] in rare high-magnitude events further reduce their reliability [6]. Extensive research has been done to make systems that analyze a variety of data sources-including seismic activity records, remote sensing imagery, and geodetic measurements-to rule out patterns or anomalies that have occurred previously in significant earthquakes. Over the past decade, ML and DL algorithms have been playing an important role in tackling the issues related to earthquake prediction systems. While the conventional prediction techniques have high false alarms, ML based methods have a higher chance of a predicting an earthquake with high accuracy [12]. Hence, this study aims to provide a comprehensive review of past research on machine learning for earthquake predictions. Traditional ML algorithms, DL algorithms and Ensemble/Hybrid Learning Algorithms have been reviewed which have proven to show high accuracy for Earthquake Early Warning Systems.

1.2 Literature Survey

To mitigate risks like seismic slope instability and soil liquefaction, engineering practice relies on a process known as Seismic Hazard Assessment. The primary outputs of this assessment are parameters like Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), and the earthquake moment magnitude (M). In the recent times, Seismic Waveforms have been used in several studies to assess the earthquake ep parameters. Seismic Waveforms data includes phase, frequency, amplitude, coherence, and shape. Seismic Catalogs have also been utilized to conduct various tests to evaluate ground movement and soil velocity. They contain data about the Earthquake magnitude, depth, longitude, latitude, location (hypocenter) and stress drop. The methods used in the selected papers are categorized based on the type of algorithms applied in each of them, broadly grouped into three categories: Traditional ML or DL or Hybrid/Ensemble.

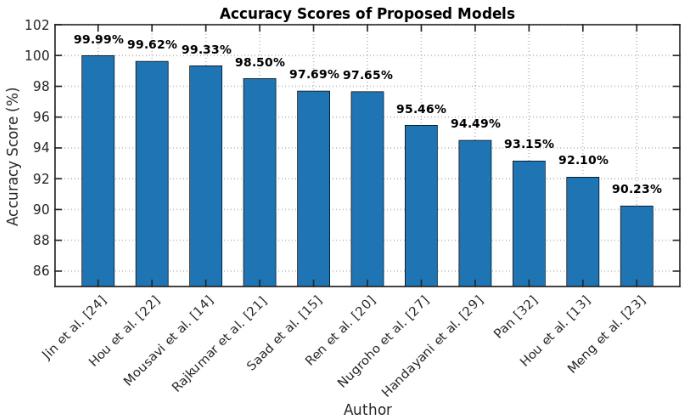

Fig. 1. Bar graph showing the Accuracy scores of the proposed models.

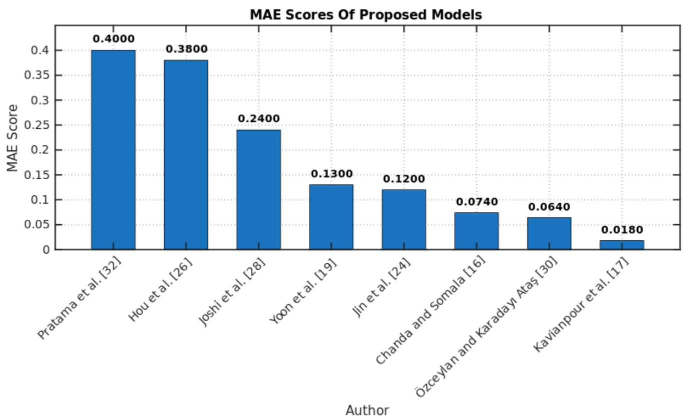

Fig. 2. Bar graph showing the (Mean Absolute Error) MAE scores of the proposed models.

1.3 Objective

The field of seismology and earthquake prediction has been revolutionized after the integration of artificial intelligence (AI) and machine learning (ML) with it. Despite these advancements, the field remains divided by inconsistent methodologies, differing datasets and the lack of standardized benchmarks. This study maps the evolving landscape by reviewing methodologies from various studies, aiming to address controversies-such as the reliability of non-seismic precursors (e.g., ionospheric TEC anomalies)-and establish a unified framework for evaluating ML's transformative potential in seismic risk mitigation.

2 Methodology

In this section, the methods implemented in the papers will be discussed separately based on the nature of the algorithm applied in their research.

2.1 Earthquake Prediction using Traditional Algorithms

For soil liquefaction triggering analysis, an accurate estimate of earthquake magnitude (M_W) is an important prerequisite. The magnitude serves as a proxy for the duration of shaking. Chanda and Somala [16] uses a SVM to predict earthquake magnitude, hypocentral distance, and elevation using synthetic vertical-component seismograms from 400 simulated earthquakes (M_W 4–7). P-S intervals, P/S-wave onsets, amplitude statistics were used as input features. The model achieved an RMSE of 0.0412 for magnitude prediction. Handyani et al. [29], RFmag model is used to predict earthquake magnitudes (M_W 3–7.6) using P-wave data from 8,527 recordings in the region of Indonesia. The model achieved 94.49% accuracy with a standard deviation of 0.36, and a MAE score of 0.22. XGBoost model was employed by [33], to predict the earthquake magnitude in North Chile using about 100,000 events from the IPOC Catalogue. The model achieves a RMSE score as low as 0.0097 and a standard deviation of 0.15.

Beyond magnitude, traditional algorithms are also used to predict ground motion intensity parameters like Peak Ground Velocity (PGV). Trained on 28,352 Japanese seismic records, a SVM model using eight P-wave parameters was employed in [13] to predict PGV. Targeting PGVs ≥8.18 cm/s, it achieved 99.62% accuracy and 95.68% precision in issuing alerts. The 20.10% false negatives pose as a challenge for high magnitude earthquake prediction.

To prioritize high risk- earthquake zones site and regional hazard screening, [32] applied LR, SVM and RF models, using data from China Earthquake Networks Center (1990–2023). LR identified five high-risk zones (Sichuan, Guizhou, Qinghai, Yunnan, Xizang) with 93.15% accuracy (AUC-ROC = 0.916). Despite strong performance, it overestimates small earthquakes and underestimates large ones due to imbalanced training data.

2.2 Earthquake Prediction using Deep Learning Algorithms

Before any detailed site-specific analysis can occur, the seismic event must be detected. A CNN-BiLSTM model was trained in [14] on 500,000 seismograms (250k earthquakes, 250k noise) from Northern California to detect earthquake signals. The model, named CRED achieves 99.33% accuracy on test data and a F-score of 99.95%. A state-of-the-art model ConvNetQuake, based on deep CNNs was designed in [15] to detect and locate earthquakes from single-station, three-component seismic waveforms. It achieved an astounding 100% event detection accuracy and 99.9% noise detection accuracy on the test set but lacked in locating the events with a mid-score of 74.5% accuracy.

Once an event is detected, the next critical step is to accurately estimate its parameters, with magnitude being an important factor. To predict the maximum magnitudes and monthly earthquake occurrences in mainland China, a CNN-BiLSTM-AM model was proposed in [17]. Using 11,442 seismic records (1966–2021), the models ended up achieving RMSE = 0.24, MAE = 0.018, and R^2 = 0.95, outperforming standalone CNN/LSTM models. Ren et al. [20], EEWMagNet, a deep learning model to classify earthquake magnitudes ($M_W \geq 4$ vs. $M_W < 4$) is created. The model achieves 90.23% accuracy. Jin et al. [35] proposes a Conformer neural network-combining convolutional and attention modules-for global and local seismic event classification and magnitude estimation. Using the STEAD and KPED datasets, the model achieved over 99.99% accuracy in event classification, indicating overfitting. It outperforms previous methods in magnitude estimation (MAE = 0.12 for STEAD, 0.19 for KPED). The Low-Rank Adaptation (LoRA) method implemented aided in reducing trainable parameters by up to 89-folds for local datasets.

Some DL models provide a more complete picture of the seismic source. A complex-valued convolutional neural network developed by Ristea and Radoi [34] processes raw 1-minute, three-component seismograms from single stations. The model estimates epicentral distance, depth, and magnitude with mean absolute errors (MAE) of 4.51 km, 6.15 km, and 0.26, respectively. It is trained on the Stanford Earthquake Dataset (STEAD). It enables rapid, accurate earthquake characterization without having multi-station data or phase arrival times.

2.3 Earthquake Prediction using Hybrid/ Ensemble Algorithms

Ensemble models showed very promising results to quantify event characteristics. Trained on the STEAD and KiK-net datasets, the Deeper CRNN model in [19] estimates the earthquake magnitude and epicentral distance using single-station, three-component seismic waveforms. The model achieved MAE = 0.1377 (magnitude), R^2 = 0.90 and 2.27 km (distance) on STEAD.

With a rapid training time of 2.44 seconds, the HEM NAEMP model devised in [30] has a hybrid ensemble model combining KNN, RF, SVM, DT and XGBoost Algorithms. It was trained on the North Anatolia and Andreas Fault Zone data, and the model achieved MSE score of 0.011, MAE score of 0.064 and R^2 score of 0.92, outperforming CNN and LSTM models. Rajkumar et al. [31], an innovative method for earthquake prediction proposes a hybrid CNN-SVM model. Results demonstrate 98.5% accuracy validated via 2-fold cross-validation.

Ensemble models also enabled identifying non-seismic precursors setting them apart from the generic ML models. Mir et al. [18] investigates the use of ensemble models and individual models to predict anomalies in soil radon gas concentration. Using real-time radon data from Muzaffarabad, the boosted tree and SVM with radial kernel achieved the best performance, with RMSLE – 0.6 and MAPE as low as 0.052.

3 Application of Logistic Regression for Soil Liquefaction Potential Assessment: A Geotechnical Perspective

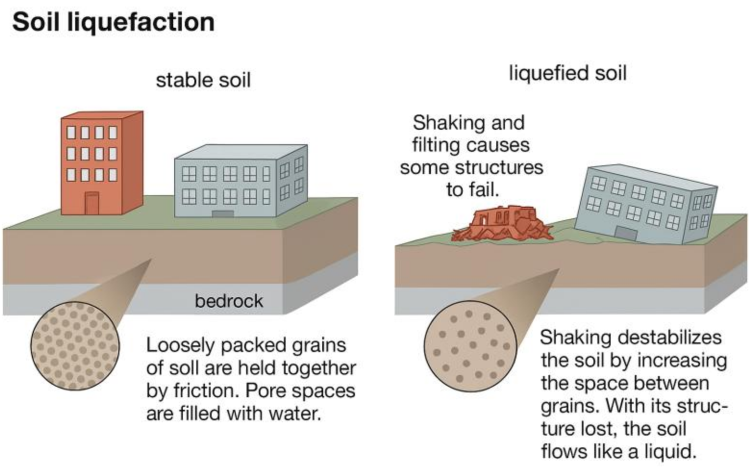

Fig. 3. Conceptual Illustration of Soil Behavior Under Seismic Loading: Stable vs. Liquefied Conditions. Adapted from *Encyclopædia Britannica 2012*

In cohesionless and saturated soils, liquefaction poses a substantial threat to the stability of foundations and infrastructure during seismic events. The identification of liquifiable zones is therefore essential for mapping out hazardous seismic zones particularly in regions with high seismicity as shown in Fig. 3. In this context, the study done by Rahman et al. (2024) [36] employs a logistic regression-based machine learning model to predict soil liquefaction potential across the area of Dinajpur Sadar, Bangladesh. The input features used used—such as penetration resistance (N1 60CS), groundwater table depth, peak ground acceleration (PGA), depth and fineness content ($F<0.0075$) are derived from in-situ Standard Penetration Tests (SPT). A detailed analysis revealed that fineness content ($r = –0.7$) and corrected penetration resistance values ($r = –0.34$) had a strong influence on the output classification as depicted in Fig. 4. The influence of other parameters such as PGA and depth was comparatively less ($r \approx \pm0.06$). For classification, a logistic regression model with hyperparameter optimization via grid search and feature scaling was used. The model achieved 93.3% accuracy and an AUC value of 0.952 on testing data. Confusion matrix analysis further aided the model to improve its accuracy, after which it accurately identified 28 of 30 samples. By integrating the significant on-site parameters into a binary classification framework, the study offered a valuable alternative to traditional and laboratory methods.

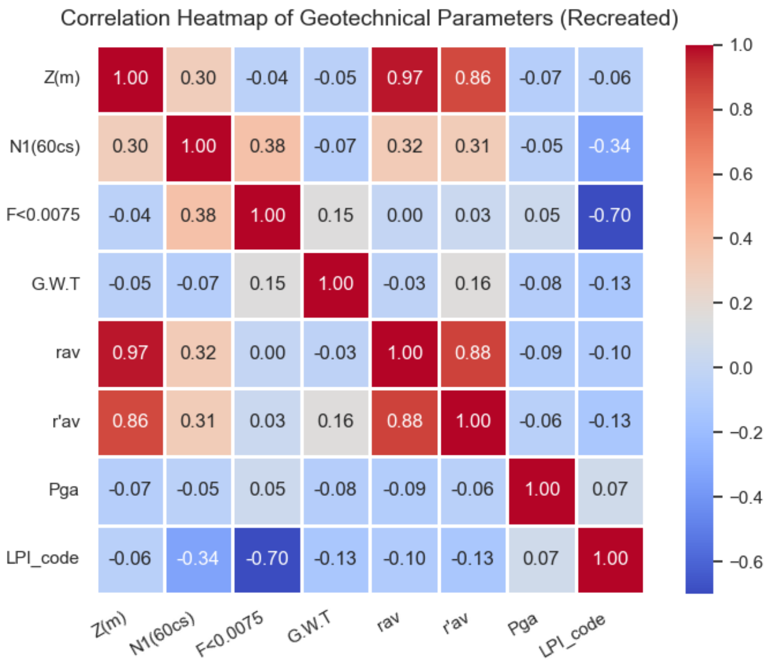

Fig. 4. Correlation heatmap of geotechnical parameters (replotted based on data from (Rahman et al., 2024))

4 Discussion

The primary geotechnical problem addressed by these AI/ML models is the assessment of seismic hazards. The reviewed studies showcased that AI and ML algorithms achieve robust performance in earthquake prediction tasks, with accuracy spanning 74.5%–100% across traditional, deep learning, and hybrid approaches. The high accuracy of Support Vector Machines (SVMs) (e.g. 99.62% accuracy in [13]) for peak ground velocity prediction is of paramount importance. Furthermore, PGV is a critical input for the seismic design of buried infrastructure, such as pipelines and tunnels, which are integral to modern society. Random Forest models like RFMag achieve 94.49% accuracy in [29] for magnitude estimation despite facing imbalances in data. Hybrid architectures like the CNN-SVM framework in [21], outperformed standalone models with 98.5% accuracy by synergizing automated feature extraction and classification.
However, even among identical algorithm types there is variability in performance. For instance, the SVM model in [16] showed contrasting results - $R^2 = 1.0$ for noise-free magnitude prediction versus 58% accuracy for azimuth estimation—highlighting the impact of feature engineering. The dataset scale also critically affects the performance of the models. Models trained on decade-long catalogue's (e.g., 114422 cases in CNN-BiLSTM-AM [17]) achieved superior stability ($R^2 = 0.95$), whereas smaller datasets aggravated underfitting, as seen in XGBoost trials using 20–35% of available data. The

creation of hybrid frameworks (e.g., HEM NAEMP [30], MSE = 0.011) and physics-guided architectures paves a pathway toward reliable prediction systems.
The use of diverse input features, such as GPS ionospheric TEC data in [15] and single-station seismic waveforms in [19], allows for a more nuanced understanding of local site effects.

5 Summary

This study directly addresses a critical challenge in geotechnical earthquake engineering: forecasting site-specific seismic behavior to ensure the safety and resilience of civil infrastructure. Its primary contribution is demonstrating how AI/ML methods can enhance seismic hazard analysis, moving beyond traditional models that struggle with the highly non-linear behavior of soil and rock during an earthquake. The application of AI/ML in seismology marks a significant shift from traditional statistical models to deep learning and hybrid models which can process non-linear data which conventional models often overlook. This approach towards seismic risk mitigation can aid us in preventing devastating consequences of high magnitude seismic events. Hybrid and ensemble architectures are resilient in showing high accuracy scores by combining spatial feature extraction and robust classification. Unique datasets, like ionospheric TEC and soil radon concentrations, expand the scope of selecting seismic precursors. Techniques such as CNNs are implemented in majority of the models, showing remarkable accuracy in classifying seismic events. Despite performance gain, these architectures face limitations in long-term forecasting. Data preprocessing, feature selection and region-specific constraints continue to be a hurdle in preparing a unified model. Hence, this paper reviewed 29 papers from academic databases, considering multiple features and datatypes. Going forward into the future, interdisciplinary collaboration, physics guided ML, and real-time models will prove to be crucial.

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