Civil Engineering Beyond Limits 1 (2026) 11114
Civil Engineering Beyond Limits
journal home: www.acapublishing.com/journals/1/cebel

Research Article

From Historical to AI-Based Approaches in Earthquake Forecasting: The Case of Türkiye

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Keywords

Earthquake,
Machine learning,
Artificial intelligence,
Magnitude prediction,
Türkiye.

Abstract

Because of the presence of active fault zones, Turkey possesses a strong seismic hazard potential. The significance of machine learning and deep learning-based techniques in understanding seismic behavior is discussed in the paper. The traditional techniques followed in earthquake prediction are also discussed in the paper. The data set required for the analysis was provided by the Kandilli Observatory and Earthquake Research Institute (KRDAE). The data set contained 66,105 earthquake data from 1900 to 2024. LSTM, Random Forest and GRU are some of the seven different techniques taken into consideration while making the assessment. The performance of the models was also compared using MAE, MSE, and RMSE. The mean squared error (MSE) calculated for the Random Forest algorithm was found to be 0.1335. The results show that deep learning and artificial intelligence-based techniques are effective in simulating small and medium-sized earthquake magnitudes and also offer a meaningful approach for predicting the magnitudes, frequencies, and locations of earthquakes.

1. Introduction

Turkey is located within Alpide-Himalayan orogenic belt. This means that Turkey is a seismically active zone. The Anatolian Plate is squeezed between the Eurasian Plate on one side and the African and Arabian Plates on the other. This has resulted in the formation of different active fault systems. The main active fault systems in Turkey are the North Anatolian Fault System (NAF), the East Anatolian Fault System (EAF), and the Western Anatolian Graben System. These faults have caused devastating earthquakes in the history of Turkey. The Erzincan earthquake of 1939, the Gölcük-Düzce earthquake of 1999, the İzmir earthquake of 2020, and the Kahramanmaraş earthquake of 2023 have resulted in loss of life and property. This shows the importance of earthquake prediction in Turkey.

Historically, earthquake predictions have been made using various approaches such as changes in seismic activity, changes in the velocity of seismic waves, electrical and magnetic field changes, and changes in groundwater activity. Nevertheless, these approaches have not been successful in predicting all major earthquakes. The only successful short-term prediction of an earthquake was the Haicheng earthquake in 1975. However, this single case does not guarantee the general effectiveness of these approaches. Hence, the short-term predictions of earthquakes are limited [1].

New ways of predicting earthquakes utilizing historical earthquake data and geographical information have come forth in the last few years thanks to artificial intelligence technologies like machine learning and deep learning. These tools can look at big data sets, find sequential time dependencies, and generate better predictions.

Research focusing on Turkey typically uses data from the Kandilli Observatory and Earthquake Research Institute (KOERI) to predict earthquake magnitude, date, location, and frequency. Ermiş and Cürebal were among the first to conduct research on Turkey and used the Decision Tree algorithm on the data for the Izmir province. The overall accuracy of the model was found to be 92%. However, the study also noted that the prediction accuracy for high-magnitude earthquakes was low [2]. Another research conducted by Karcı and Şahin found that LSTM model was more accurate than traditional machine learning models. This was due to the ability of the LSTM model to handle time-series data. [3].

Doğan et al. [4] evaluated various machine learning algorithms for Northwestern Turkey and revealed that techniques such as Bayesian Ridge, Elastic Net, XGBoost, and Gradient Boost could accurately identify focal sites in accordance with active fault segments. Demirelli et al. [5] indicated that the integration of earthquake catalog data with geological and geodetic data markedly diminished prediction errors when employing Random Forest and XGBoost models.

In global research employing deep learning, LSTM and GRU models are dominant. Kaş et al. [6] indicated that the GRU model exhibited reduced error levels and enhanced stability compared to LSTM when utilized with Turkish data. Research conducted in China, the United States (Los Angeles), and Malaysia indicates that Random Forest, LSTM, and GRU models attain good accuracy [7, 8, 9]. The Random Forest model attained an accuracy over 97% in predicting short-term (30-day) earthquake categories [7].

Previous studies have generally examined earthquakes in Turkey and worldwide on a regional scale. However, this study will be conducted in a holistic manner, keeping in mind factors like the magnitude of the earthquake, their frequencies and the location of the earthquake within the general boundaries of Turkey. Moreover, the model for earthquake prediction will be developed based on the model that provides the best

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Received 28 Jan 2026; Revised 04 Feb 2026; Accepted 04 Feb 2026
https://doi.org/10.36937/cebel.2026.11114

results during the performance evaluation. The fundamental aim of the study is to overcome the limitations of traditional methods and to perform earthquake prediction using current technological advancements and artificial intelligence-based models.

2. Methods

2.1. Historical Earthquake Prediction Methods

Historically, several approaches have been taken to attempt to predict earthquakes. The approaches taken to predict an earthquake can be summarized as changes in seismic activity (foreshocks), changes in seismic waves, changes in electrical and magnetic properties, as well as changes in groundwater dynamics. However, none of these approaches can be taken as a tool to predict an earthquake [1].

Foreshocks have been described as small earthquakes that take place prior to the main shock and around the epicenter. However, it has also been noted that not all major earthquakes have foreshocks. Moreover, it is still not easy to predict if a small earthquake has the potential of becoming a major one. This has greatly reduced the usefulness of foreshock analysis. In addition, studies carried out in the 1970s in the former Soviet Union showed slight reductions in the velocities of seismic waves months, and even a year, prior to a major earthquake. However, this was not consistently confirmed.

Changes in electrical conductivity, irregularities in electric fields, and changes in magnetic fields have also been observed as potential causes of earthquakes. These events are believed to be associated with stress building along fault zones or the movement of deep underground fluids. Although large changes have been detected in the vicinity of a few large earthquakes, the statistical validity of these changes as a predictive tool is not clear. Also, changes in groundwater levels, flow rates, and chemical content, particularly increases in the concentration of radon gas, have also been observed as precursors of earthquakes. However, these changes are not consistent and are not observed for all earthquakes [1].

The main finding of these investigations is that there is no one precursor or group of precursors that always happens before an earthquake. Hence, the prediction of earthquakes in the short term is not possible, and some researchers have suggested that earthquakes cannot be predicted at all, considering the decades of research that have gone into the field.

The only generally reported effective earthquake prediction happened in Haicheng, China, in 1975. Seismic activity, groundwater level changes, and unusual animal behavior were collectively used as indicators. As a result, the population was evacuated from the area. Consequently, when the earthquake hit the area soon thereafter, the loss of life was significantly diminished. However, this was followed by an unsuccessful prediction in 1976 when the major earthquake that hit the area in China, known as the Tangshan earthquake, was not predicted. Predictions based on time for the Parkfield segment of the San Andreas Fault in the US also did not come true as planned [1].

Historical earthquake prediction methods rely heavily on physical observations and past events (e.g., foreshocks or crustal deformations), limiting the reliability of predictions in cases of data deficiencies or errors. In contrast, AI-based methods are capable of predicting not only earthquake magnitudes but also their frequency and potential locations.

Traditional approaches to earthquake prediction are based on historical data and some physical indicators, which are often not enough to describe how earthquakes work. However, with the increase in the availability of data and computing resources, artificial intelligence-based methods have been proposed as the most promising ones for earthquake prediction. The machine learning and deep learning techniques offer a more efficient solution for earthquake prediction using the available data. The effectiveness of machine learning and deep learning–based approaches for earthquake prediction was evaluated by taking into account the limitations of traditional forecasting methods.

2.2. Machine Learning and Deep Learning–Based Methods

There are different methods to construct models for predicting earthquakes, including Random Forest, Decision Tree, SVM, kNN, LSTM, XGBoost, and GRU. The results of performance evaluation indicated that the best models were Random Forest, LSTM, and GRU.

- Random Forest Algorithm

Random Forest is a machine learning approach that uses a group of models to handle both classification and regression tasks. The method builds several decision trees by using bootstrap sampling on the original dataset. This makes the model better at generalizing. Random Forest is different from regular decision trees because it only looks at a random selection of features at each node to get the best split. This approach lowers the correlation between individual trees and lowers the possibility of overfitting [10]. The algorithm works in three basic steps. In the first step, a certain number of bootstrap samples are selected. Second, a decision tree is created for each bootstrap sample. Finally, the final output is made by combining the predictions from all the trees [11]. There are a few hyperparameters that affect the performance of the Random Forest model directly [12]. For this research, the hyperparameters that are used in the model for the forecasting of earthquake magnitudes, frequencies, and locations are the number of trees (n_estimators ranging from 0 to 200), the maximum depth of the tree, the number of features to consider at each split (max_features), the minimum number of samples required to split an internal node (min_samples_split ranging from 0 to 20), and the minimum number of samples required at a leaf node (min_samples_leaf ranging from 0 to 20). One of the critical aspects of the Random Forest model is the determination of the optimal number of trees. Adding more trees usually makes predictions more accurate, but the extra benefit tends to go away beyond a certain point.

- Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks were introduced in 1997 as a solution to the limitations of Recurrent Neural Networks, which were not able to remember information over large periods of time. Because of their unique cell structure, LSTM networks can keep and process long-term relationships. This makes them great for predicting time series and modeling complicated dynamic systems. Memory cells that store long-term information are the most important part of the LSTM architecture. The cell has two basic parts: the cell state and the hidden state. The cell state contains relevant information from the past time steps, while the hidden state looks at the most recent input and helps make predictions for the future step [13]. LSTM networks use three gate control mechanisms: forget gate, input gate, and output gate. The forget gate controls what needs to be forgotten from the past. The input gate controls how much needs to be added from the present. Finally, the output gate controls what needs to be passed into the next hidden state. LSTM networks learn long-term temporal patterns well using these methods [14].

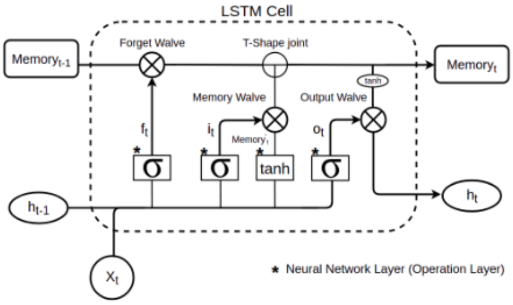

Figure 1. Structure of LSTM neural network cell [15]

- Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is another type of recurrent neural network with a less complex structure compared to the LSTM model. GRU doesn't have a separate cell state like LSTM. Hence, all the information is passed through the hidden state. This helps the model to manage the balance of the past information with the newly received information [14]. GRU has two gates: update gate and reset gate. The update gate decides how much previous information is being stored in the model and how much new information is being added. The update gate should have a high value in order to store previous knowledge, which allows learning of long-term dependencies. On the other hand, if the update gate has a low value, new information will have a greater impact. The reset gate decides how much previous information is being ignored. When the reset gate has a low value, previous information will have a reduced effect, which is important in learning short-term dependencies [14]. The vector of the input at time 't' (x_t) holds the information at a given time, and the previous hidden state (h_{t-1}) holds all the information learned until then. These two are then used to update the hidden state, which is the memory of the network [14].

2.3. Dataset

The dataset has information on a total of 66,105 earthquake records, ranging from the year 1900 to 2024. The magnitude of the earthquakes ranges from 3.0 to 8.0. The primary data source for this paper was obtained from Boğaziçi University Kandilli Observatory and Earthquake Research Institute (KRDAE). Additional data on high-magnitude earthquakes, i.e., xM > 5.0 before 1900, were obtained by conducting an extensive literature survey from NCEI Global Historical Hazard Database. The number of earthquakes with high-magnitude (xM > 5.0) is 1308. The dataset consists of earthquake data including date, magnitude, and location (latitude and longitude).

Table 1. Dataset

Date	Latitude	Longitude	xM	Date	Latitude	Longitude	xM
2024.12.31	37.8838	29.2558	3.2	1907.12.01	37.6000	34.5000	6.3
2024.12.31	38.2770	38.6010	3.2	1906.12.28	40.5000	42.0000	6.0
2024.12.31	38.0710	37.5068	4.0	1906.09.28	40.5000	42.7000	6.2
2024.12.31	38.4138	38.9583	3.0	1905.12.04	39.0000	39.0000	6.8
2024.12.31	38.4087	38.9415	3.2	1904.08.18	38.0000	27.0000	6.0
2024.12.30	39.4170	37.2977	4.3	1904.08.11	37.7000	26.9000	6.2
2024.12.30	40.7775	31.0195	3.2	1903.04.28	39.1000	42.5000	6.3
2024.12.30	36.4533	44.4900	3.2	115.12.13	36.100	36.100	7.5
2024.12.30	36.7442	30.1467	3.9	407.04.01	41.000	29.000	6.6
2024.12.29	40.5958	36.7083	3.3	447.01.26	40.900	28.500	7.3
2024.12.29	35.3395	26.3260	3.0	478.09.25	40.800	29.200	7.2
2024.12.29	35.1408	27.2722	4.3	525.05.29	36.250	36.100	7.0

2.4. Performance Evaluation

The evaluation of the performance of models is of critical importance in choosing the most suitable models for prediction. Thus, the performance of the models is evaluated using the error metrics of regression models, which are MAE, MSE, and RMSE. MAE provides a clear accuracy metric by calculating the average absolute difference between predicted and observed values, treating all errors as equally significant. MSE calculates the average of the squared errors of prediction, which gives more importance to larger errors and enables a deeper analysis of the model. RMSE, which is the square root of MSE, is highly sensitive to large errors and is very effective in identifying models that make large errors in their predictions. However, because it is sensitive to outliers, it is best used with other metrics to get the most information. The formulas for performance metrics are below:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid \tag{1}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

where y_i is the value that was observed, $\hat{y}_i$ represents the predicted value, and n is the number of observations.

3. Results

As it was mention before there were a few algorithms that used for earthquake forecasting work and their performance results illustrates below:

Table 2. Algorithms Performance Results

Algorithm	MSE	MAE	RMSE
LSTM	0.2640	0.3718	0.5134
Random Forest	0.1335	0.2652	0.3654
SVM	0.1467	0.2594	0.3830
kNN	0.1600	0.2873	0.4001
Decision Tree	0.1481	0.2741	0.3848
XGBoost	0.1390	0.2642	0.3684

Among the machine learning techniques applied, Random Forest algorithms achieved high prediction accuracy for small- and moderate-magnitude earthquakes. The dataset was divided into 70% training (45 346), 20% validation (12 963), and 10% testing (6 472). Analysis showed that the best performance was achieved according to the MSE criterion, with an error value of 0.1335. The model, developed using the Random Forest algorithm, produced meaningful outputs regarding earthquake frequency for Turkey as a whole. The results contribute to determining earthquake frequency values in different regions. In this context, some key findings from the model are summarized below:

Table 3. Frequency Results

Latitude	Longitude	Magnitude	Average Frequency Days
37.778	29.317	4.9	2893
36.705	30.500	5.1	2636
41.500	44.215	4.9	23367
40.399	26.280	3.8	7362
40.817	34.806	3.7	1120
39.695	39.545	5.4	1328
40.460	27.208	5.4	2027

The ensemble structure of the Random Forest method, which integrates multiple decision trees, resulted in more robust and generalizable predictions compared to individual tree-based models. Optimization of both the number of trees and feature selection contributed to reducing overfitting and improving overall predictive performance. These findings indicate that classical machine learning approaches are well suited for modeling short-term and frequently occurring seismic events.

Deep learning architectures, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, exhibited superior capability in modeling long-term seismic trends due to their ability to capture sequential temporal dependencies. The LSTM model demonstrated strong predictive performance by retaining long-range information through its gating mechanisms. As a result of the analyses, the best performance was obtained according to the MSE criterion, and the error value was calculated as 0.264. The hyperparameters chosen were epochs 50 and batch size 32. On the other hand, the GRU model had a more compact architecture and fewer parameters (40 epochs and 8 batch sizes). This made it more efficient and faster to train while still being accurate.

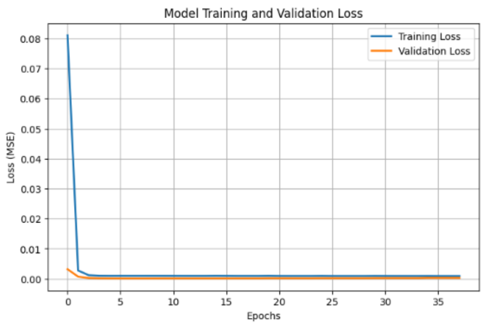

Figure 2. GRU Model Training and Validation Loss

One important finding from the analysis is that the GRU model could make useful predictions for earthquakes with a magnitude of 6.0 or higher. Even though there aren't many high-magnitude events to use for training models, the GRU was able to learn both short- and long-term dependencies at the same time. This demonstrates that the GRU model is relevant not only to common, low-magnitude earthquakes but also to rare, high-magnitude seismic occurrences.

4. Conclusion

The results obtained in this study have shown that artificial intelligence-based algorithms provide a preliminary method for earthquake prediction in terms of location, magnitude, and frequency. By using different algorithms, it was identified that the Random Forest algorithm was appropriate for small-magnitude earthquakes, whereas the GRU algorithm was appropriate for large-magnitude earthquakes. After the exploring a huge number of literatures and comparing the results with this study, it has been emphasizing that the level of uncertainty in the predictions concerning large-magnitude earthquakes is higher compared to that of small and moderate earthquakes. This is due to the statistical rarity of large earthquakes, the complexity of fault segment behavior, and the inability of the modeling framework to capture local geological conditions. Hence, the results should be seen as signs of a higher risk of earthquakes, not exact predictions of when and where they will happen. Moreover, Random Forest generates point-specific predictions. It cannot learn spatial correlation.

Though the results are obtained from the models such as LSTM, GRU, and Random Forest in the forecasting of earthquake magnitude, location, and frequency, there are some limitations associated with the methods, considering the nature of the data. The rarity of large-magnitude earthquakes can lead to insufficient representation of such events by the models, and increase the risk of overfitting, especially in high-parameter deep learning models like LSTM and GRU. Therefore, the risk of overfitting should be kept under control. The unequal distribution of catalog data can cause models to over-learn dense earthquake records in some locations and make predictions less accurate in areas with sparse data. From the geological perspective, the high-risk zones predicted by both GRU and LSTM models are highly spatially consistent with active fault zones in Türkiye which are North Anatolian Fault System (NAF), the East Anatolian Fault System (EAF), and the Western Anatolian Graben System. This indicates that the output of the deep learning models is generally consistent with the known tectonic features and thus valid for seismic hazard assessment. Moreover, it might also be a good idea to add extra parameters to the dataset for further study, such as depth, changes in sea level, and levels of radon gases emissions and make a forecasting in these areas as well.

Declaration of Conflict of Interests

The authors declare that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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How to Cite This Article

Khurshudov, E., Arslan, A., From Historical to AI-Based Approaches in Earthquake Forecasting: The Case of Türkiye, Civil Engineering Beyond Limits, 1(2026),11114.
https://doi.org/10.36937/cebel.2026.11114