

Evaluation of datasets and deep learning methods used in earthquake prediction in the context of the February 6, 2023 earthquake

Deprem tahmininde kullanılan veri setleri ve derin öğrenme yöntemlerinin 6 Şubat 2023 depremi açısından değerlendirilmesi

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Abstract

On February 6, 2023, Türkiye experienced its most severe earthquakes in over 80 years, beginning with a 7.8 (Mw) earthquake, followed by two consecutive 7.5 (Mw) earthquakes nine hours later. The most distinctive feature of this earthquake compared to others is not only that it was more destructive than the others, but also that its impact covered a vast geographical area. There are many studies on earthquake prediction; these studies address topics such as emergency preparations and response planning, risk analysis, or damage estimation. Due to the success of deep learning (DL) algorithms in various fields, using DL methods in earthquake prediction has become a very popular research topic in recent years. Studies using DL methods for earthquake prediction were examined in terms of the DL algorithms and data sets used, with a focus on whether the earthquakes that occurred on February 6, 2023 and after could be predicted before the earthquake occurred. According to the findings suggest that ionospheric reactions observed before and after the earthquake and the use of the earthquake time series that occurred before the earthquake can be used to predict future earthquakes. However, these results are still preliminary predictions, therefore, it is crucial to expand the early warning system network and to increase the accuracy of real-time prediction models using DL algorithms. Additionally, this study aims to guide future research through a multidisciplinary review of the existing literature. Ultimately, such work will help improve prediction models and contribute to better preparedness for earthquake risks.

Keywords: Deep learning, Earthquake prediction, February 6, 2023, Earthquake datasets.

Öz

Türkiye 6 Şubat 2023'te 7.8 (Mw) büyüklüğünde depremin ardından dokuz saat sonra büyüklüğü 7.5 (Mw) olan art arda iki deprem ile 80 yılı aşkın süredir Türkiye'de yaşanan en şiddetli depremleri yaşamış oldu. Bu depremi diğer depremlerden ayıran en belirgin özellik sadece diğerlerinden daha yıkıcı olması değil aynı zamanda etki alanının oldukça geniş bir coğrafyaya yayılmış olmasıdır. Deprem tahmini ile ilgili oldukça fazla çalışma bulunmaktadır, bunlar acil durum hazırlıkları ve müdahale planlamaları, risk analizi veya hasar tahmini gibi konuları ele almaktadır. Derin öğrenme algoritmalarının birçok alanda elde ettiği başarılı sonuçlarda, deprem tahmininde derin öğrenme yöntemlerinin kullanımı son yıllarda oldukça popüler bir araştırma konusu haline gelmiştir. Deprem tahmini için derin öğrenme yöntemlerini kullanan çalışmalar incelenmiş ve bunun sonucunda kullanılan derin öğrenme algoritmaları ve veri setleri incelenerek 6 Şubat ve sonrasında gerçekleşen depremlerin, deprem gerçekleşmeden önce tahmin edilip edilemeyeceği sorusuna yanıt aranmıştır. Elde edilen bulgulara göre hem deprem öncesinde hem de sonrasında 'iyonosferik tepkilerin' varlığı ve depremden önce gerçekleşen deprem zaman serisinin kullanımı ile gelecekteki depremlerin tahminlerinin yapılabileceği sonucuna ulaşılmıştır. Ancak buralardan elde edilen sonuçlar tahmin mahiyetindedirler bu sebepten erken uyarı sistemleri ağının genişletilmesi ve gerçek zamanlı çalışan derin öğrenme algoritmaları ile yapılan tahmin sistemlerinin doğruluğunu artırmak oldukça önemlidir. Ayrıca literatürün farklı bakış açısını içeren multi disiplinler yaklaşımıyla inceleyerek gelecekte yapılacak çalışmalara rehberlik etmek amaçlanmaktadır. Sonuç olarak bu tür bir araştırma daha iyi tahmin modelleri geliştirilmesine yardımcı olarak toplumların deprem riskine karşı daha hazırlıklı olmasına katkı sağlayacaktır.

Anahtar kelimeler: Derin öğrenme, Deprem tahmini, 6 Şubat 2023, Deprem veri setleri.

1 Introduction

Earthquakes are among the most devastating natural disasters, having caused significant loss of life and property throughout human history. Beyond the immediate human toll, they lead to the collapse of buildings and infrastructure, causing long-term socioeconomic disruptions. To mitigate these risks, measures such as advanced warning systems and structural reinforcement should be taken to reduce earthquake risks. Additionally, advances in fields like modern technology and DL can offer new opportunities for earthquake prediction and risk analysis. Despite these advances, there is no definitive method for predicting earthquakes with precision, including factors like intensity, location, depth, and timing. This uncertainty stems

from the complex and poorly understood factors that trigger earthquakes, whether linear or non-linear [1].

To date, scientists have not been able to predict major earthquakes but have instead estimated the probability of an earthquake occurring. A meaningful prediction must include specifics like date, time, location, and intensity; however, pinpointing the exact moment of a strong earthquake remains a challenge. As more earthquake-related parameters are identified, prediction accuracy is expected to improve [2].

According to USGS data, approximately 700 shocks occur annually in inhabited areas, though very few of them are felt by people. In recent years, the establishment of networks of seismic recording devices has made it possible to detect and

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record even minor tremors [3]. Additionally, ML algorithms have shown promising results in distinguishing environmental noise from seismic signals. Once seismic signals are isolated, prediction models can more accurately analyse subsurface changes [4].

Earthquake predictions fall into two main categories: short-term, which focuses on immediate warnings, and long-term, which analyzes environmental and seismic change activity to predict earthquakes expected to occur over an extended period.

Earthquake prediction methods can be categorized into four groups: precursor signal research, traditional machine learning (ML) algorithms, mathematical analysis, and DL algorithms [5].

Problems such as fatalities, disabilities, psychological effects, housing crises, disruptions to education, and lack of access to clean water can be alleviated by reducing the destructive impact of earthquakes through widespread implementation of early warning systems and improving predictive accuracy. Moreover, addressing the negative impacts of earthquakes on people and governments globally requires Global Seismic Monitoring Networks (GSN), which will enhance data sharing and research collaboration, thus improving predictive models.

Better results have been achieved by using DL methods to distinguish mixed signals in monitoring seismic data collected for early warning systems. Based on the patterns of continuously occurring small earthquakes, researchers have concluded that the rise and fall of earthquake correlations are linked to the accumulation and release of stress caused by tectonic activity [6]. This approach, based on the correlation of small earthquake patterns, can be used to apply regression analysis to time series data using DL algorithms, similar to a study conducted by Kervanci, Akay, and Özceylan (2024), and positive results can be obtained. Future predictions made with time series containing data over certain time intervals have generally yielded good results [7].

The datasets in earthquake prediction typically consist of data related to seismic activity, crustal movements, geological features, and various other parameters. These datasets are diverse and can be obtained from a wide range of institutions and organizations. Some common sources include seismic activity data from geological survey agencies, geodetic data from research institutions or universities, and historical earthquake records from national geological organizations. The most important factor affecting the success of a DL algorithm is the data itself. While seismology is rich in data, the lack of high-quality labeled datasets, inconsistencies in labeling accuracy, and lack of standardization in metrics impact the speed of research and limit the comparability of results. To address these challenges, two datasets were prepared on a global scale, including the Stanford earthquake dataset (STEAD) [8], which includes local earthquakes and high-quality seismic noise. Many studies have utilized this dataset in DL methods, including [9],[10], and [11]. Although the dataset contains data from January 1984 to August 2018, it was updated in 2020 and has not been updated since then. Therefore, its use for predicting on February 6, 2023, earthquake should be evaluated for future years' predictions.

Additionally, satellite imagery and remote sensing data collected by space agencies can be used to monitor tectonic movements. Overall, the sources of earthquake prediction datasets are diverse and may include government agencies, research institutions, universities, and international organizations, such as the European-Mediterranean

Seismological Centre (EMSC), The National Earthquake Information Center (NEIC), USGS, the Japan Meteorological Agency (JMA), and the California Institute of Technology (Caltech) Seismological Laboratory. In Türkiye, earthquake data can be accessed from two main sources: the Disaster and Emergency Management Presidency (AFAD) and Boğaziçi University Kandilli Observatory and Earthquake Research Institute. Additionally, the earthquakes of August 17 and November 12, 1999, raised significant concerns in Istanbul and the Marmara Region. In response, the "Earthquake Emergency Response and Early Warning System" was established by Boğaziçi University Kandilli Observatory and Earthquake Research Institute in 2002, following a decision by the Council of Ministers, as part of the country's earthquake preparedness efforts. In the remainder of this paper, the literature review section is organized under subheadings and focuses on the datasets utilized in earthquake prediction. Studies employing machine learning (ML) algorithms are summarized in Table 1, while those specifically addressing the February 6, 2023 earthquake are detailed in Table 2. The Results and Discussion section will analyze the studies related to the prediction of the February 6, 2023 earthquake, exploring the challenges of earthquake prediction. It will also evaluate the datasets and methodologies that could enhance future earthquake predictions in Türkiye.

2 Literature review

DL methods have attracted great attention thanks to recent technological developments. Due to their promising results in various fields, DL algorithms have also been applied to earthquake prediction. Although a complete technique has not yet been developed for earthquake prediction many studies aim to reduce uncertainties. The use of DL methods in these studies offers significant potential for earthquake prediction. It is expected that such studies conducted to reduce uncertainties in prediction will contribute to more effective measures against earthquakes in the future. Researchers have applied various ML and DL algorithms, such as Random Forest (RF), Pattern Recognition Neural Network (PRNN), Gradient Boosted Regression Trees (GBRT), Recurrent Neural Network (RNN), Naïve Bayes (NB), Linear programming Boost Ensemble Classifier (LPBoost), K-Nearest Neighbors (KNN), Logistic Regression (LR), Hill Climbing (HC), Decision Tree (DT), Multiple Linear Regression (MLR), Support Vector Machine (SVM), Naive Bayes (NB), Stochastic Gradient Descent (SGD), a Bayesian Belief Network (BBN), Linear Discriminant Analysis (LDA), Back propagation neural network (BP), Multi-Layer Perceptron (MLP), Light Gradient Enhancement Machine (LGBM) to predict earthquake occurrences, damage, and seismicity. In addition to the algorithms, datasets also play a critical role in earthquake prediction. During the literature review, studies related to earthquake prediction are examined under subheadings based on the datasets used, providing a more structured analysis.

2.1 Laboratory earthquake simulation data

For instance, [12] used the RF method in their study investigating the prediction of when damage will occur by using only acoustic signals in laboratory earthquake simulation. The experimental results where they applied RF method, where the test dataset was not used in model training, is quite successful with R-squared score (R^2) = 0.89. Thus, they reported that they provided accurate fault predictions based on instantaneous analysis of the acoustic signal.

Table 1. Summary of literature review.

	Models	Results	Datasets
[16]	SVM	classification Accuracy=98%	226 seismic soil liquefaction from [15]
[12]	RF	R2 =0.89	Data from a well-characterized laboratory system
[20]	LPBoost ensemble, RF, RNN, PRNN	Accuracy=79%	Hindukush region seismically activity dataset from Hindukush and United States Geological Survey.
[5]	LSTM (two layers)	Accuracy=85.12%	USGS
[22]	Hierarchical K-means clustering	Cluster-1 Results TP=2, TN=424, FP=2, FN=61	Indonesian Agency for Meteorological, Climatological and Geophysics (BMKG) and USGS
[21]	Tree-based ML clustering algorithm	Accuracy=70%	Seven different datasets from [28], [29], and [30]
[13]	GBRT	R = 0.3	Data from the laboratory system
[31]	ANN, RF, and SVM	ANN, SVM and RF with MCC value of 0.601, 0.630, and 0.724 respectively.	Cyprus region seismic data from Cyprus earthquake catalog.
[17]	LR, BP, MLR, DT, KNN, SVM, and NB.	AUC values respectively for datasets 0.91733, 0.99535, and 0.97926,	Three different datasets from [32], [15], and, [18]
[33]	SVM	MCC=0.72806	GNSS network, EPN, and NASA Goddard Space Flight Center OMNIWeb
[14]	LGBM and lots of other algorithms	Test MAE= 2.2650 OA= 97.4790%	The laboratory seismic data of small samples.
[19]	K2, hill climbing (HC), tree augmented naive (TAN) Bayes, and Tabu search		9 earthquakes in different parts of the world between 1964 to 1989.
[34]	SVM, LSTM, RF, and LDA	Accuracy=0.703 %	TEC data from http://ionolab.org/ earthquake data from https://earthquake.usgs.gov/ Awaran earthquake TEC data from GNSS
[35]	LSTM	RMSE= 3.2582 MSE= 10.6162	
[24]	singular spectrum analysis (SSA), ARIMA, CNN, and LSTM	MSE of ARIMA=0.0324 SSA=0.0229 CNN=0.03 LSTM=0.01	Average and maximum earthquake dataset between 1900-2019
[25]	CNN+GRU, RF, ARIMA, CNN, and GRU	MSE=1220365.74	NEIC 1965 to 2016 earthquake >=5.5
[26]	DLPGA based on CNN	MCC of DLPGA=0.8384 and Pd=0.6195	650 stations of the National Institute of Earth Science and Disaster Resilience Research (KiK-net) in Japan
[37]	STDEV and NARX	They detected abnormal fluctuations over the earthquake epicenter 6 to 7 days ago	AP, RH, OLR, and AT from NOAA (National Oceanic and Atmospheric Administration) Physical Sciences Laboratory (PSL), TEC from GNSS, STS from Japan Aerospace Exploration Agency (JAXA), LST from MODIS (Terra) satellite, and earthquake dataset from USGS

Table 2. Earthquake prediction methods about the 6 February 2023 earthquake.

	Methods	Models	Results	Datasets
[27]	Structural integrity status of buildings after earthquake	RF, KNN, LR, DT, SVM, SGD, MLP	Accuracy=93%	Structural integrity status of the buildings near the 44 AFAD stations.
[36]	Anomaly detection	LSTM, ACO, Kalman Filter, median method, and MLP	The result obtained from TEC dataset is that abnormal behaviors started to be observed 10 days before the earthquake.	USGS, GIM-TEC satellite dataset NASA
[38]	Mathematical pattern recognition algorithms	Kora-3 pattern recognition algorithm	It was concluded that earthquakes of magnitude=6.5 and above are connected to morpho-structural nodes.	Based on morpho-structural zonation dataset by IM Gelfand, VI Keilis-Borok and colleagues in 1973
[39]	DL image segmentation for the identification of collapsed buildings	PSPNet, LinkNet, U-Net, and FPN	Accuracy of U-Net=0.970 LinkNet=0.969 FPN=0.973 PSPNet=0.963	Maxar and Planet Earthquake Zone satellite images.
[40]	statistical methods	partial statistical methods	Seismic electrical activities indicating the onset of seismicity three and a half months before the earthquake.	NTA's Seismic Electrical Signals (SES)
[41]	ML and ANN	XGBoost, LGBM, CatBoost, ET, RF, BR, DT, ANN	MSE=0.0607, RMSE=0.2464, R2=0.2010, MAE=0.1997	USGS dataset from January 2015 to February 2023
[42]	They were able to obtain a smaller TEC perturbation from the Mw 5.6 earthquake.	TEC time derivative and D1-GNSS-RT	They were able to obtain a smaller TEC perturbation from the Mw=5.6 earthquake.	CYPOS GNSS network

Regarding the estimating the time and magnitude of earthquakes for laboratory earthquakes, they reported that they obtained a good generalization result by using GBRT algorithm to obtain the result of $R^2 = 0.3$ using the complex surface deformation history [13]. Also, they reported accurate

earthquake magnitude and timing estimations using the GBRT algorithm for the next experimental earthquake.

Rouet-Leduc et al. compiled the results they obtained from the competition they held by sharing only a small part of the laboratory seismic data on Kaggle between January 10, 2019

and June 3, 2019. While the best Mean Absolute Error (MAE) value fell to 1.080 on the last day of the competition from the data set consisting of 13% of the test data set, the best MAE value was 2.2650 for the 87% data set they called the "private leader board". Since the dataset was not stationary, it caused a difference between the training and test results, which is an indication of over fitting. The winner of the competition achieved the best result using the LGBM with triple mixed cross-validation [14].

2.2 Soil liquefaction

In their study, the authors used SVM analysis on a dataset obtained from [15], which consists of 133 liquefied, and 93 non-liquefied soil samples collected from 52 regions affected by six different earthquakes. After normalizing the dataset containing six input variables, which they considered as a classification problem, between 0 and 1, they conducted experiments for different parameters of the dimension (power) d , and the penalty parameter C . They concluded that the C parameter was not very sensitive to the classification results [16].

For predictions, they first combined three soil liquefaction datasets from previous studies [17]. They employed seven different algorithms for these predictions: LR, BP, MLR, DT, KNN, SVM, and NB, using the Area Under the Curve (AUC) score metric. One of these datasets included 620 soil liquefaction samples collected from earthquakes in Türkiye and Taiwan. The second dataset contained 226 liquefaction samples obtained from the paper published in 2003 [15], and the third included 185 soil liquefaction datasets from [18]. Additionally, they combined three soil liquefaction datasets with the location and magnitude of all major earthquakes of magnitude 5.5 and above that occurred worldwide from 1965 to 2016.

For parameter learning, they used K2, Tree Augmented Naive (TAN) Bayes, HC, and Tabu Search, employing the Netica software with a BBN. To compare the results, they used four different outcome metrics: F-measure, Overall Accuracy (OA), Recall, Precision, and AUC. They found that cone tip resistance and vertical effective stress were the most sensitive parameters for estimating liquefaction from six different features in seismic soil liquefaction datasets collected from nine earthquakes occurring from 1964 to 1989. The best results were achieved with K2 and TAN Bayes, yielding an OA value of 97.4790% [19].

2.3 Seismic activity

They evaluated earthquake prediction results using ML classifiers LPBoost ensemble, RF, RNN, and PRNN with seismic activity dataset from Hindukush and United States Geological Survey. To analyze the results of the classification model, they evaluated them in terms of performance evaluation criteria such as sensitivity, specificity, correct and incorrect prediction values, which are widely used in earthquake prediction studies. They achieved the best accuracy results of 79% with PRNN and LPBoost ensemble [20].

In the paper where they proposed a spatiotemporal approach for earthquake prediction due to crustal motion, they proposed an LSTM structure that can learn not only earthquakes that occur in a certain region but also two-dimensional relationships between earthquakes at different locations. They assigned earthquakes that occurred in the regions they divided into rectangular study areas using latitude and longitude information to the areas they determined. They created an event frequency matrix for each time interval and region. They employed the Softmax activation function, which is commonly

used in classification tasks, and applied dropout to prevent over fitting in the cascaded LSTM structures. This allowed the model to retain temporal dependencies of LSTMs across each sub-region. In order to separate unrelated sub-regions, they put sub-regions within the same fault zone into the same group and to get better results, so they divided the Chinese mainland into 9 regions and predicted earthquakes over 4.5 from 1966 to 2016 and achieved 63.50% overall prediction accuracy but all region overall prediction accuracy is 85.12% [5].

In the paper where they obtained new dataset groups by using an ML clustering algorithm to characterize seismic indicators for earthquakes, they used seven different datasets from Japan, Iberian Peninsula, and Chile. After determining the seismic features and the most characteristic features of large earthquakes containing n previous events ($n=50$), they created the model called precursor tree by selecting general precursors and shared that they achieved 70% and above accuracy in general [21].

Shodiq and colleagues used Hierarchical K-means clustering, a clustering algorithm, to predict the aftershock that will occur 5 days after a certain threshold value. In the study, where they first determined the optimum number of clusters, then performed the clustering process and visualized these results, they obtained better results in experiments where the threshold value was 6 or higher [22].

The dataset obtained from the Cyprus earthquake catalogue is cleaned from artificial or man-made seismic activity, and they used Artificial Neural Networks (ANN), RF, and SVM where they made earthquake predictions for multiple Threshold Magnitudes (TM) and multiple Forecast Periods (TP). In the problem they considered as a binary classification problem, experiments were conducted with prediction periods of 5, 7, 10, 15 days later and it was observed that MCC values significantly increased as the prediction period extended. It was also observed that the performance decreased with increasing threshold magnitude [20].

In their paper on earthquake magnitude estimation, they determined the basic features using the feature extraction method from earthquake precursor signals obtained from an electromagnetic sensor. Then, they used the data obtained from the space satellite regarding earth activities in the classification. Finally, they trained the dataset they prepared using noise simulation and SMOTE oversampling technology on the CNN network they proposed for the earthquake magnitude classification problem [23].

In the earthquake prediction study covering a 200 km region in the Aegean region of Türkiye, they used traditional methods such as Autoregressive Integrated Moving Average (ARIMA) and Singular Spectrum Analysis (SAS), and DL methods such as CNN and LSTM. They organized the medium-sized earthquakes that occurred between January 1970 and December 2020 monthly. So LSTM achieved the best results in their predictions for the next 36 months. Mean Squared Error (MSE) values for each method are LSTM = 0.0100, SSA = 0.0229, CNN = 0.0300, and ARIMA = 0.0324 [24].

Using the dataset consisting of earthquake records of magnitude 5.5 and above from NEIC between 1965 and 2016, they compared the hybrid CNN+GRU model with the RF, ARIMA, CNN and GRU models with MSE, Root Mean Squared Error (RMSE), MAE, and Mean Absolute Percentage Error (MAPE) metrics and concluded that CNN+GRU outperformed other models [25].

They used a dataset of 3271 earthquake events with magnitudes between 4 to 9 from 650 stations of the National Institute of Earth Science and Disaster Resilience Research (KiK-net) in Japan. They used an end-to-end DL model (DLPGA) based on CNN to estimate the peak ground acceleration (PGA) using the feature parameters of the P wave obtained from the on-site earthquake early warning (EEW) systems. They compared their method with the peak displacement (Pd) commonly used in earthquake prediction. They concluded that the accuracy of distinguishing the destructiveness of ground motion was improved by 35-150% [26].

2.4 Other datasets

Furthermore, Senkaya and others where they evaluated the damage status of the stations in the February 6, 2023 earthquake zone, they applied ML algorithms RF, KNN, LR, DT, SVM, SGD, and MLP to the damage status of the stations in the north, south, east and west directions. As a result of 5-fold cross-validation, they achieved 93% accuracy, which is the best result from RF. However, since this dataset contains station data and there are a limited number of stations, the data set is quite limited. By obtaining them from the Damage Assessment Inquiry systems, 44 stations belonging to AFAD, and the structural integrity status of the buildings close to these stations [27].

To determine the time periods for the probability of a devastating earthquake like the one that occurred on February 6, along the East Anatolian Fault System-where the Arabian, African, and Anatolian plates converge-mathematical pattern recognition algorithms were applied. Specifically, the morpho-structural zoning Kora-3 pattern recognition algorithm, developed by IM Gelfand, VI Keilis-Borok, and colleagues in 1973, was used to analyze earthquake centers with magnitudes ≥ 6.5 . The analysis suggested that earthquakes are likely to occur at certain points with a probability of a magnitude 6.5 or higher in the identified locations, confirming the thesis of morpho-structural nodes [38].

In another study, the performance of four deep learning models-Pyramid Scene Parsing Network (PSPNet), LinkNet, U-Net, and Feature Pyramid Network (FPN)-was evaluated for identifying collapsed buildings in satellite images following the February 6 earthquakes. Although this study did not focus on earthquake prediction, it used deep learning methods for post-earthquake damage assessment and was therefore included in the analysis [39].

Nicholas (2024) explored the use of Seismic Electrical Signals (SES) from NTA to estimate the probable location, time, and magnitude of impending earthquakes. The study detected crustal movements associated with strong earthquakes, using partial statistical methods. The dataset from this study has the potential to be further analyzed with deep learning algorithms and is therefore relevant to the discussion [40].

Biswas et al. demonstrates a comparative analysis of several machine learning algorithms for predicting outcomes using a dataset spanning January 2015 to February 2023. The researchers evaluated performance using algorithms such as XGBoost, LightGBM, CatBoost, Extra-Trees Regressor (ET), Random Forest Regressor (RF), Bayesian Ridge Regressor (BR), Decision Tree Regressor (DT) and three different Artificial Neural Network (ANN) algorithms. The best training result they achieved was with $R^2 = 0.99$ and 0.98 . The error metrics they used for evaluation were MSE, R^2 , RMSE and MAE. The team applied these models to a test period from March 1 to March 31,

2023, and found that the LightGBM model performed best, with $MSE=0.0607$, $RMSE=0.2464$, $R^2=0.2010$, $MAE=0.1997$ [41].

Another study by [42] examined the CSID dataset on Total Electron Content (TEC) to assess ionospheric responses to the February 6 earthquake and its aftershocks. A strong ionospheric response was observed following the first earthquake, while weaker responses were noted after three aftershocks. Although the study did not investigate potential precursor distortions in TEC dataset prior to the earthquake, the findings support the use of TEC data in future earthquake prediction models.

In summary, Table 1 highlights valuable insights into the use of ML and DL for earthquake prediction. However, there are significant opportunities for improvement in terms of dataset size, evaluation metrics, real-world applicability, and model interpretability. The comparability of these models is also limited due to inconsistent metrics. Integrating diverse datasets could lead to more comprehensive earthquake forecasts through multidisciplinary approaches, although most studies to date have used only one or a few datasets together for ML predictions.

Table 2 includes studies on the February 6, 2023 earthquake. It is seen that mathematical, seismic and deep learning approaches are used for earthquake prediction in these studies. TEC, morpho-structural dataset, satellite images and seismic signals are the main datasets used to predict the occurrence of earthquakes. Different models and methods offer significant advances in earthquake prediction, but it is clear that datasets need to be further diversified and improved.

3 Conclusions

The situation of bridges, telecommunications, airlines, public institutions, hospitals, etc. structures that need to continue to be used after the February 6, 2023 earthquake has shown that the use of seismic performance enhancing technologies in newly constructed structures is essential [43]. Earthquake prediction is crucial for preparing communities for potential earthquake risks. Accurate predictions allow timely warnings and the creation of emergency plans, helping to minimize both loss of life and property damage. Furthermore, long-term earthquake predictions can aid in urban planning, identifying high-risk areas, and enabling appropriate safety measures. Earthquake prediction is particularly important for countries like ours, which are located in seismically active regions, including Taiwan, Southern California, Iran, Japan, Indonesia, and Türkiye. Following the recent major earthquakes, seismic datasets have increasingly been used to predict future earthquakes, complemented by improved methods. The studies summarized in Table 1 highlight the potential of deep learning (DL) techniques in advancing earthquake prediction capabilities. In Türkiye, estimating earthquake magnitudes using DL algorithms, combined with parameters such as historical dataset, sensors, magnetic and electric waves, and seismic indicators, is critical. Expanding sensors networks and modernizing the technological infrastructure will facilitate more accurate and real-time predictions. This paper has reviewed various ML and DL techniques applied to earthquake prediction, particularly for the February 6, 2023 earthquake in Table 2. Although these predictive models have made progress, challenges such as datasets limitations, overfitting, and the complexity of seismic systems remain. For example, ionospheric responses such as TEC disturbances reported by Maletckii and colleagues at Table 2. provide valuable clues but

are not consistently observed before each earthquake. We also see that the popular approach of using time series of seismic activity in past years, has not been used in the February 6, 2023 earthquake prediction except Biswas, and colleagues. In addition, combining historical earthquake datasets, seismic, ionospheric, and satellite datasets show potential to improve predictions, but there are difficulties in dataset integration and no studies combining the dataset. In addition, limited region-specific datasets, especially for high-risk areas such as Türkiye, hinders the generalizability of these models.

Future research has the potential to achieve better prediction results by focusing on hybrid models and optimization techniques that integrate seismic, ionospheric, and geographic datasets for improved prediction accuracy. It is also important to address overfitting issues and expand region-specific datasets, especially for earthquake-prone areas. Improving sensors networks and modernizing technological infrastructure will enable more accurate and real-time earthquake predictions and reduce the risk of loss of life and property in future earthquakes.

4 Author contribution statements

All contributions to this article belong to İlkay Sibel Kervanci.

5 Ethics committee approval and conflict of interest statement

"The prepared article does not require approval from the ethics committee". "The article was written with no conflict of interest with any individual or organization".

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