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REVIEW

A systematic review of Earthquake Early Warning (EEW) systems based on Artificial Intelligence

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Abstract
Early Earthquake Warning (EEW) systems alarm about ongoing earthquakes to reduce their devastating human and financial damages. In complicated tasks like earthquake forecasting, Artificial Intelligence (AI) solutions show promising results. The goal of this review is to investigate the AI-based EEW systems. Web of Science, Scopus, Embase, and PubMed databases were systematically searched from its beginning until April 18, 2023. Studies that used AI algorithms to develop EEWs and forecast earthquake magnitude were qualified. The quality assessment was conducted using the Mixed Methods Assessment Tool version 2018. Detailed analysis was performed on 26 of 2604 retrieved articles. Researchers predict earthquakes most often using neural network family models (21 studies). Among eight categorized groups of parameters for earthquake forecasting, it was often predicted utilizing seismic wave characteristics (65.38%) and seismic activity data (61.54%). AI models most often predicted earthquake magnitude (32.69%) and depth (15.38%). Logistic Model Tree and Bayesian Network had the highest sensitivity, accuracy, and F-measure efficiency (99.9%). Findings showed that AI algorithms can forecast earthquakes. However, additional study is needed to determine the efficacy of more data-driven AI algorithms in mining seismic data using more input variables. This review is helpful for seismologists and researchers developing EEW systems using AI.

Keywords Earthquake forecasting · Earthquake Early Warning system · Artificial Intelligence · Seismic data mining

Introduction

Earthquakes are a daily occurrence worldwide, affecting every region of the globe (Anders 2013). While they vary in intensity, not all earthquakes are perceptible to humans. However, large earthquakes with a magnitude of 7 or higher happen more frequently than once a month (Burnett and Mothorpe 2021). In 2021, the world experienced a total of 2,206 earthquakes with a magnitude of five or higher (Department 2023; Salam et al. 2021). Japan, Indonesia, southern California, Turkey, Iran, and Taiwan are recognized as some of the most seismically vulnerable locations on Earth (Salam et al. 2021). The impact of large earthquakes can be devastating, leading to irreversible damage to human

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lives, financial resources, and infrastructure within a matter of seconds (Essam et al. 2021; Salam et al. 2021).

Hence, the primary objective of Early Earthquake Warning (EEW) systems (Heaton 1985; Kilb et al. 2021; Meier et al. 2020; Wald 2020) is to provide advance notice regarding the potential occurrence of large earthquakes. EEWs serve as a short-term strategy for mitigating earthquake risks by delivering rapid and reliable predictions of impending seismic events (Satriano et al. 2011). By offering timely warnings, EEWs enable individuals and institutions to implement protective measures and minimize the extent of damage caused by earthquakes (Dallo et al. 2022; Liu et al. 2022; Salam et al. 2021). However, earthquake prediction poses significant challenges. On one hand, issuing false alarms in the absence of an actual earthquake can lead to societal panic and economic disruptions. On the other hand, failing to provide warnings about the possibility of a significant earthquake can have catastrophic consequences (Berhich et al. 2021; Pirmagomedov et al. 2018).

The effectiveness of EEW systems primarily relies on striking a balance between two key factors: (1) the precision of the source parameter, encompassing magnitude, location, and ground motion estimates generated by the underlying EEW algorithm, and (2) the promptness with which the system issues an alert (Cremen et al. 2021).

The prediction of earthquake magnitudes can be achieved through various methods such as sensor technology, devices, magnetic and electrical wave analysis, or seismic indicators utilizing historical data (Asim et al. 2017; Salam et al. 2021). A significant portion of magnitude prediction algorithms relies on establishing a relationship between the earthquake magnitude and specific parameters manually identified in relation to the initial P-wave (Wang et al. 2023).

The most valuable data for earthquake prediction stems from previous seismic information combined with real-time monitoring of the Earth's surface. It has been observed that the accuracy of earthquake forecasts improves with the utilization of larger datasets (Dimililer et al. 2021; Pirmagomedov et al. 2018). Seismologists have employed various approaches, including geophysical, mathematical, statistical, and computational models, in their pursuit of earthquake prediction (Berhich et al. 2021; Salam et al. 2021). However, achieving precise predictions has proven challenging, predominantly due to the intricate computations involved and occasional difficulties in analyzing vast volumes of recorded seismic data (Berhich et al. 2021; Chin et al. 2019).

Artificial Intelligence (AI) techniques have emerged as powerful tools capable of addressing complex and challenging problems (Berhich et al. 2021). These methodologies offer the potential to enhance the accuracy, speed, and scalability of big data analytics (Rahmani et al. 2021). Consequently, numerous researchers have turned to AI-based data mining methods to tackle earthquake prediction, leveraging the stochastic nature and meta-parameterization qualities of earthquakes (Liu et al. 2022; Mousavi and Beroza 2020; Mousavi et al. 2019a; Murwantara et al. 2020; Nakano et al. 2019; Perol et al. 2018; Ross et al. 2018; Ross et al. 2019; Zhu et al. 2019).

Prior reviews have examined various aspects of EEW systems, such as user requirements and earthquake estimation models (Allen and Melgar 2019), AI-based ground motion models (Cheng et al. 2023), algorithms for rapid prediction of seismic-source parameters and ground shaking, as well as predicted earthquake effects (Cremen and Galasso 2020), EEW systems based on Internet of Things (IoT) and cloud infrastructure (Abdalzaher et al. 2023), earthquake prediction through the prediction of magnitude, signal discrimination, electron density in the ionosphere, and radon gas anomalies using machine learning (ML) and deep learning algorithms (Gürsoy et al. 2023), and earthquake prediction methods utilizing AI models (Al Banna et al. 2020; Galkina and Grafeeva 2019; Mignan and Broccardo 2020).

Considering the multitude of factors that influence the performance of AI-based EEWs, this review aims to address the following goals:

- To identify and classifications of factors used to predict earthquake intensity in artificial intelligence models.
- To distinguish and categorize of AI algorithms used to predict earthquakes.
- Reporting the efficiency of the used AI models with earthquake prediction aim.

Methods

The authors of this comprehensive review adhered to the guidelines specified in the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement, ensuring a rigorous and transparent methodology.

Search strategy

To identify relevant papers, an extensive electronic search was performed on four prominent databases, namely PubMed, Embase, Scopus, and Web of Science, up until April 18, 2023. The search strategy employed a two-fold approach, incorporating two sets of keywords: (1) Artificial Intelligence keywords, and (2) Earthquake-related keywords. The specific search query utilized for PubMed is shown in Table 1.

The search process followed specific inclusion and exclusion criteria as outlined below:

Inclusion Criteria:

1. Papers that detail the utilization of artificial intelligence or machine learning methods in the development of EEW systems.

Table 1 Search query related to PubMed

Database	Search query
PubMed	("Earthquakes"[Mesh] OR Earthquake*[tiab]) AND ("Machine Learning"[Mesh] OR "Unsupervised Machine Learning"[Mesh] OR "Machine Learning"[tiab] OR "Supervised Machine Learning"[Mesh] OR (Learning[tiab] AND Machine[tiab]) OR (Learning[tiab] AND Transfer[tiab]) OR "Artificial Intelligence"[Mesh] OR "Artificial Intelligence"[Mesh] OR "Artificial Intelligence"[tiab] OR "early warning system*"[tiab] OR (Intelligence[tiab] AND Artificial[tiab]) OR (Computational[tiab] AND Computational[tiab]) OR "Computational Intelligence"[tiab] OR "Machine Intelligence"[tiab] OR "Computer Reasoning"[tiab] OR "Computer Vision System*"[tiab])

2. Papers published in the English language.
3. Papers published up until April 18, 2023.

The exclusion criteria were as follows:

1. Papers that did not employ artificial intelligence for EEW systems.
2. Papers whose primary focus did not revolve around the utilization of artificial intelligence or machine learning for EEW systems.
3. Conference papers.
4. Review papers.

Following the completion of the search, the identified papers were imported into EndNote software, where any duplicate papers were eliminated. Subsequently, two researchers independently assessed the papers for adherence to the inclusion and exclusion criteria.

Quality assessment

In order to evaluate the methodological quality of the studies included in this review, the Mixed Methods Assessment Tool (MMAT) version 2018 (Hong et al. 2018) was employed. The MMAT tool is specifically designed for the critical appraisal of primary studies within mixed systematic review studies. It is suitable for methodological appraisal of experimental, observational, and simulation studies. The MMAT checklist consists of 6 sections including: (1) screening questions (for all types of studies), (2) Qualitative, (3) Quantitative randomized controlled trials, (4) Quantitative nonrandomized, (5) Quantitative descriptive, and (6) Mixed methods. MMAT questions have three choices answers consist of "yes", "No", and "can't tell". When a criterion in a question wasn't reported clearly in a paper, the "can't tell" option is selected. The first section consists of two screening questions for all types of studies. If the answer of each of them for a specific paper is "No" or "can't tell", this means that the MMAT checklist isn't suitable for methodological appraisal of this paper. Totally, 25 questions are existed in other five sections (each section has five questions). Considering the types of included studies in this research (quantitative description studies), the questions of the screening section and fourth section were used.

Characteristics and technical aspects of the included studies

This study focused on analyzing the publication trend related to earthquake prediction using AI methods and highlighted the countries where the first authors were based. It systematically extracted the technical components of AI-based EEW systems from the included studies. These components encompassed the size of the datasets used, the target variables investigated, the machine learning techniques applied, and the performance metrics evaluated. By examining these elements, the study provided valuable insights into the advancements and trends in AI-based EEW systems.

Results

Search results

The initial search across the databases yielded a total of 2,604 articles. After eliminating duplicates, the titles and abstracts of 1,980 articles were screened. Subsequently, the researchers conducted a thorough review of the full texts of 64 articles, ultimately including 26 studies for data analysis. The various stages of the review process are visually represented in Fig. 1, utilizing the PRISMA 2020 diagram.

Quality assessment

The result of the methodological assessment of the included articles is illustrated in Fig. 2. As shown in this figure, the most problematic area of included studies was nonresponsive bias in two studies. One of these studies (Liu et al. 2022) had a low value of efficacy metrics, and the other one had a high value of error measurement criteria (Salam et al. 2021). The non-representativeness of the selected sample was the other problematic methodological issue of AI-based EEW research (two studies (Marhain et al. 2021; Samui and Kim 2014) had not mentioned their

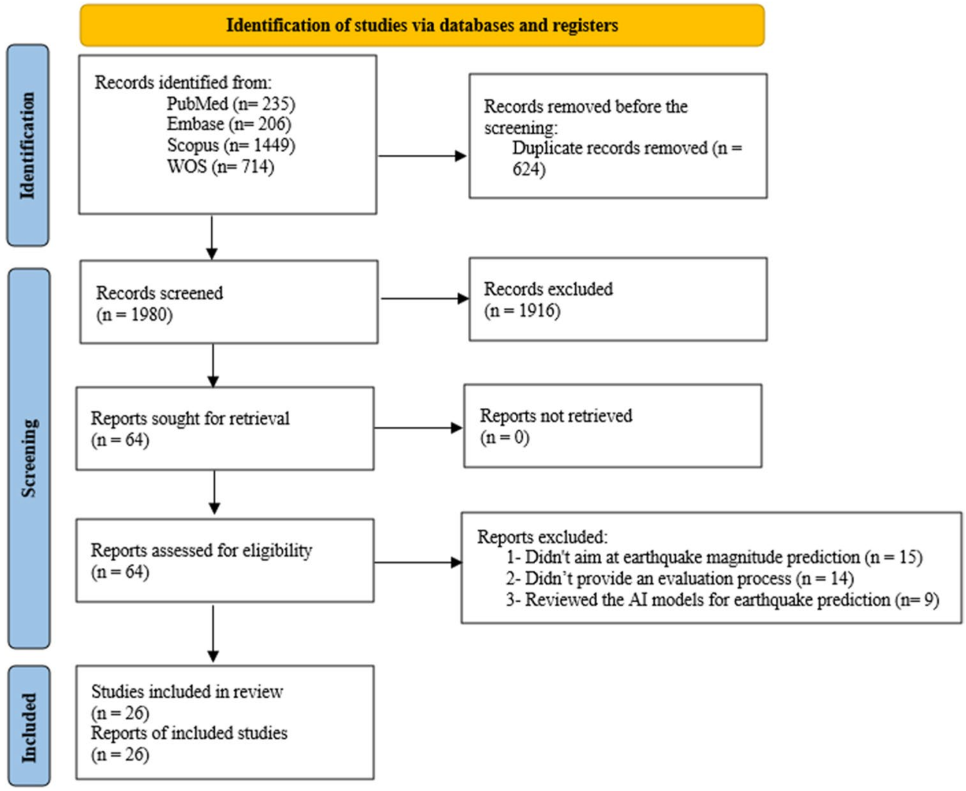


Fig. 1 PRISMA 2020 diagram for systematic review studies which included searches of databases

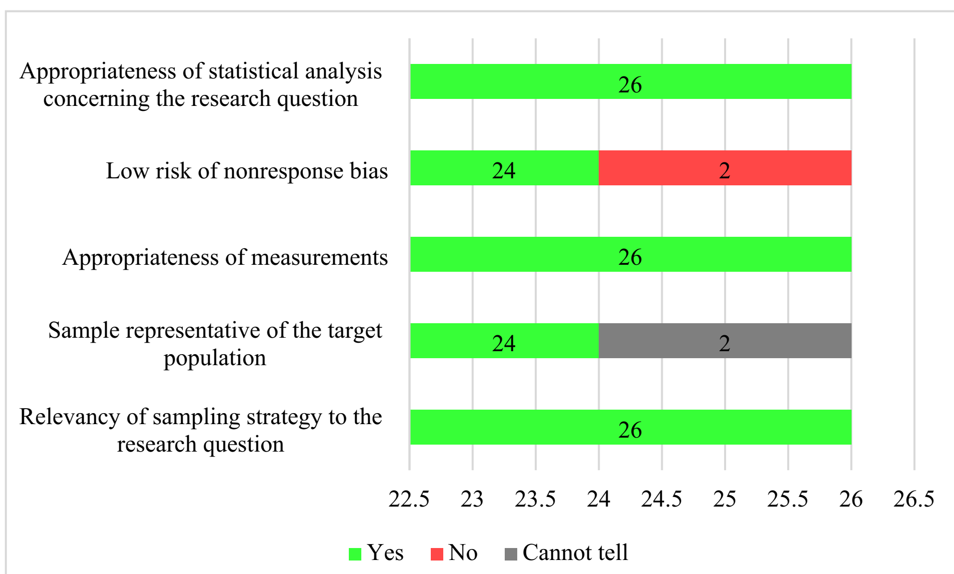


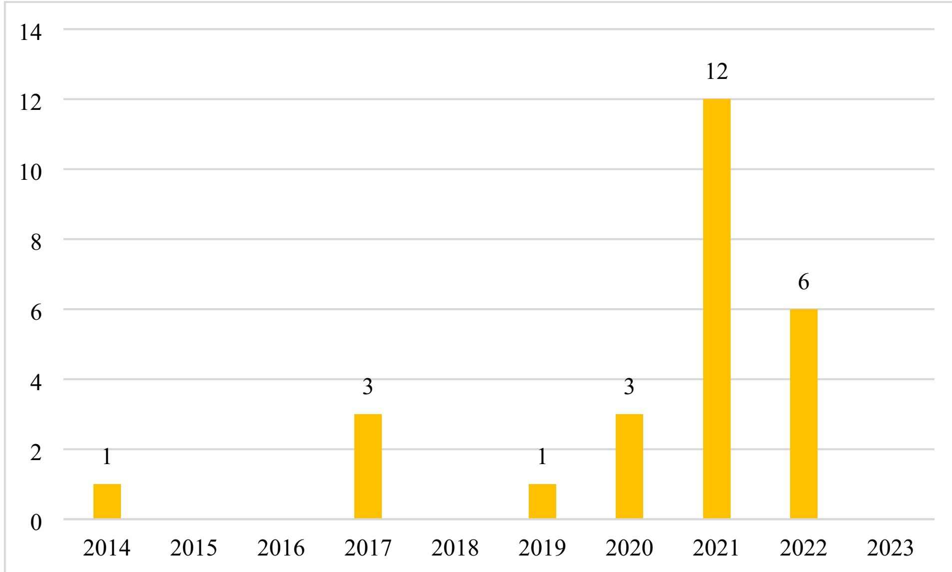
Fig. 2 Quality appraisal of reviewed papers

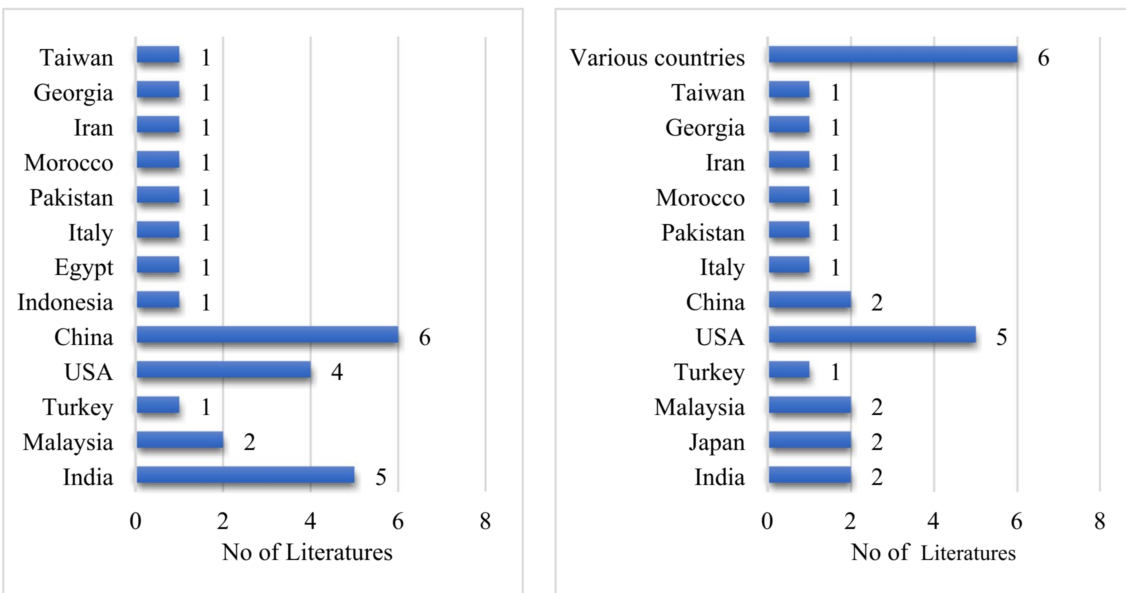
sample size, Table 5 in Appendix). All the reviewed studies have used statistical and mathematical computations related to AI techniques to answer their research question, used variables for developing their selected AI models have been clearly explained, and collected meteorological, seismological, and earthquake data samples that are relevant to their research question.

Characteristics of the included studies

The characteristics of the included studies were succinctly summarized in Table 5, located in the Appendix. Figure 3 illustrates the publication distribution of the reviewed articles, revealing that around 70% of the articles were published in 2021 and 2022. Notably, no articles related to the

Fig. 3 Publication year of the reviewed studies





a first author's countries frequency of reviewed studies

b dataset's countries frequency of reviewed studies

Fig. 4 Countries of the reviewed studies

topic were published in 2015, 2016, 2018, or during the period of the research until its completion in 2023.

The comprehensive review of articles has unveiled that a total of 13 countries have conducted studies on earthquake prediction utilizing AI methods. Figure 4 (part a), shows the countries that have conducted these studies. Most of the studies have only examined data related to one country (Fig. 4, part b). The China (six publications), India (five papers), and United States (four studies) have published most of studies, respectively. However, researchers mostly used the seismic data from several regions of world (six studies) as well as USA seismic datasets (five studies).

Technical aspects of AI-based EEW systems

Table 2 provides insight into the dataset sizes used in the development of EEW systems. The majority of studies (57.69%) have used datasets larger than 1,000 records. Also, two studies (Essam et al. 2021; Salam et al. 2021)

Table 2 Datasets size that each study used to develop an AI-based EEW

Dataset size	Frequency	Minimum	Maximum
[1–1,000)	7	27	773
[1,000–2,000)	6	1,404	1,903
+2,000	9	4,931	150,000

reported their dataset size through time duration of their sampling from earthquakes-related signals with a specific time interval.

The analysis of the included studies revealed that each study employed specific target features related to earthquakes for training and testing their AI models. Among these features, magnitude (13 studies) and depth (8 studies) have been used more than others. Additionally, a few studies explored the utilization of various other features to develop intelligent EEW systems. Figure 5 visually presents the target features employed in each study, providing a comprehensive overview of the diversity of target features used in earthquake prediction research.

Based on the reviewed articles, several predictors have been mentioned in the context of predicting earthquakes using AI. As shown in Table 3, magnitude predictors were categorized into eight groups. The frequency of each category was depicted in Fig. 6. A study belongs to a category if it used at least one of this category factors as magnitude predictor. The most commonly used predictor was the time, which was part of the "Seismic Wave Characteristics" group and accounted for approximately 54% of the cases. Other frequently used predictors included depth and magnitude, both of which were part of the "Seismic Activity Data" group and accounted for 50% of the cases. The velocity included in the "Ground Motion Data" group were used in 19.2% of the cases.

To provide a comprehensive overview of the AI algorithms employed in the included studies, they were categorized into families, as outlined in Table 4. For instance, if a study utilized a modified version of the SVM algorithm known as Least Square Support Vector Machine (LS-SVM), it would be categorized under the SVM family. Table 4 presents the different types of algorithms within each family, along with their respective frequencies.

According to Table 4, among the algorithms in the NN family, the most frequent one was the artificial neural network (ANN) with a frequency of 3 studies, while in the SVM family, the most frequent one was the SVM algorithm with a frequency of 6 studies. As depicted in Table 4, the AI algorithms most frequently discussed across the body of reviewed literature and their relative frequencies of appearance are portrayed. It should be noted that the total number of algorithms represented is not equivalent to the total number of studies surveyed, as multiple algorithms were often employed within a single research effort. The aim in compiling this data was to account for all algorithms referenced across the studies, rather than exclusively highlighting the highest performing technique in each respective work. This more comprehensive enumeration provides useful insight into the state-of-the-art by documenting the relative popularity and exploration of different machine learning approaches over time within the given family. The neural network (NN) family has the highest frequency at 43%, followed by the support vector machine (SVM) family at 16.3%. The Decision Tree (DT) family has the lowest frequency at 8%.

The evaluation of algorithms employed in EEW systems has encompassed a range of performance metrics. Through

Fig. 5 Target features of the reviewed studies. PGA: Peak Ground Acceleration

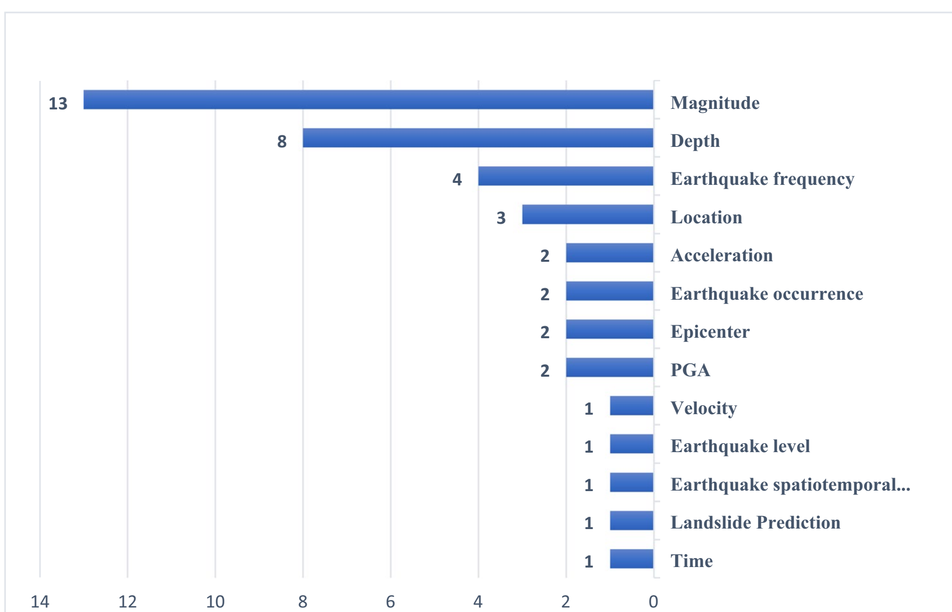


Table 3 Categorization of magnitude predictor factors

Predictors category	Included factors
Seismic Activity Data	Earthquake presence, Earthquake intensity, Magnitude, Average magnitude, Magnitude distribution, Magnitude error, Magnitude changes (ΔM), The difference between the maximum observed and the maximum occurred earthquake magnitude, Type of seismic event, The rate of square root of seismic energy release, Square root of released seismic energy during time, Hypocentral depths, Depth error
Seismic Wave Characteristics	P-wave time window, Travel time residual, S-Wave, P-wave, P-wave index value (PIv), Surface wave, μ(meantime), Deviation from Mean time between characteristic events, Average period (τc), Predominant period (τp)
Seismic Network Data	Seismic network densities/configurations
Seismic Analysis Parameters	Focal mechanisms (based on average strike, dip, and rake values), b_value (the slope of the curve between the log of frequency of occurred earthquakes and the earthquake magnitude given from Richter inverse power law), η value (sum of mean square deviation based on inverse power law), Comprehensive parameter, Product parameter (TP), Peak ratio (Tva), Deviation of actual data from the Gutenberg–Richter inverse power law, Seismicity precursor, Autocorrelation function (ACF), Consecutive monthly frequency data up to six consecutives data values, FD parameter
Displacement Data	Peak displacement (Pd), Displacement squared integral (ID2), Cumulative vertical absolute displacement (cvad), Ratio of peak ground velocity with peak ground displacements (Tvd)
Ground motion Data	Peak ground acceleration (PGA), Cumulative vertical absolute acceleration (cvaa), Velocity, Peak velocity (Pv), Velocity squared integral (IV2), Cumulative absolute velocity (CAV), Cumulative vertical absolute velocity (cvav), Velocity models
Geographical Data	Latitude, Longitude, Elevation, Slope, Curvature, Horizontal distance between the epicenter and station, Distance from fault, Distance from the road, Distance from the river, Reservoir depth (H), Length, Width
Environmental Data	Lithology, Soil type, Land use type, Topographic wetness index, Water level in wells, Tidal variations, Local magnetic field components, Hourly geomagnetic DST index, Ultra-low frequency electromagnetic anomalies, Signal-to-noise ratio

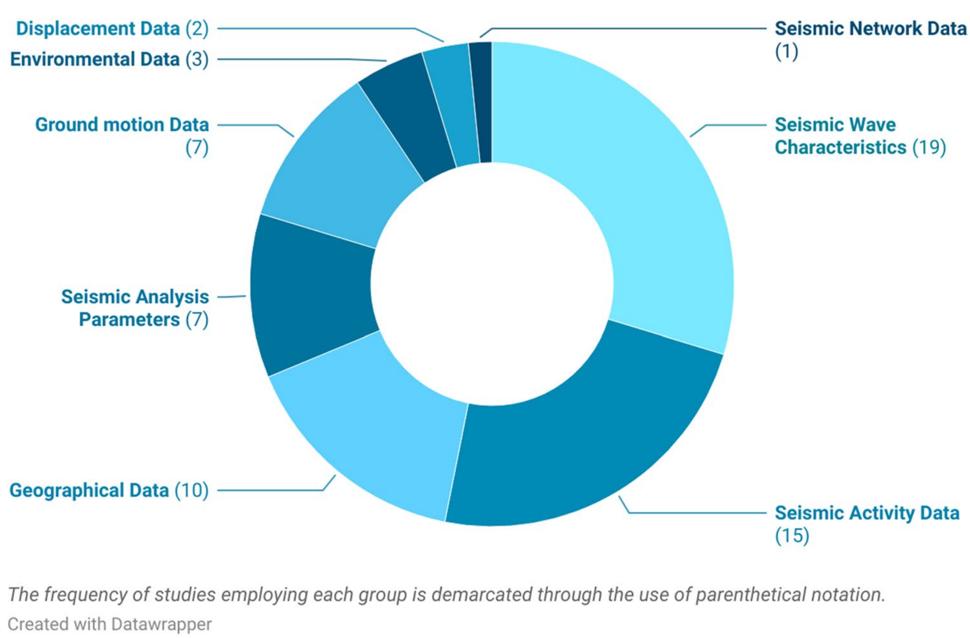


Fig. 6 Classification of magnitude predictors in EEWs

the review of included studies, it was observed that certain metrics were more commonly utilized than others. Specifically, Mean Absolute Error (MAE) and accuracy were the most frequently used metrics, appearing in 8 studies each. Root Mean Square Error (RMSE), recall/sensitivity, and precision were also commonly employed, featuring in 5 and 4 studies, respectively. For further details regarding these measures and their corresponding values, please refer to Table 5 in the Appendix, which provides comprehensive information on the evaluation of algorithms in EEWs.

Figure 7 presents the efficiency of used algorithms based on different criteria to determine their reliability and

Table 4 Types of algorithms available in each family of artificial intelligence algorithms considered for early earthquake prediction

Family name of algorithms	Shallow (classic, traditional)/ Deep learning algorithms	Supervised/ Unsupervised algorithms	Types of algorithms related to each family: frequency	No. of algorithms/Total
DT-Family	Shallow learning algorithms	Supervised learning algorithms	Decision Tree: **1**, LightGBM: **1**, Boosted Decision Tree Regression (BDTR): **1**, Random Tree: **1**	8%
RF-Family			Random Forest: **5**, Random Forest Regression (RFR): **1**	12.3%
Baysian Family			Naïve Bayes: 2, Bayesian Network: 1, Bayesian framework: 1; Bayesian Deep Learning with Convolutional Neural Network: 1	10.2%
SVM-Family			SVM: **6**, Least Square Support Vector Machine (LS-SVM): **1**, FPA-LS-SVM (which is a hybrid of flower pollination algorithm (FPA)and the least square support vector machine (LS-SVM): **1**	16.3%
Logistic Regression-Family			Logistic Regression: **2**, Multinomial logistic regression: **1**, Linear Regression: **1**, Logistic Model Tree (LMT): **1**	10.2%
NN-Family		Both supervised and unsupervised learning algorithms	Artificial Neural Network: 3, Graph Neural Network: 1, Pattern Recognition Neural Network: 1, Radial Basis Function Neural Network (RBFNN): 1	43%
	Deep learning algorithms		LSTM: **3**, Bidirectional LSTM (BiLSTM): **1**, Convolutional Neural Network: **1**, Fully Convolutional Network (FCN): **1**, Deep Neural Network: **1**, Batch Normalization Graph Convolutional Neural Network (BNGCNN): **2**, BNGCNNAtt (Batch Normalized Graph Convolutional Neural Network with Attention Mechanism): **1**, Graph Convolutional Neural Network (GCNN): **1**, GCNNAtt (Graph Convolutional Neural Network with Attention Mechanism): **1**, Multilayer Perceptron Neural Network (MLPNN): **1**, Recurrent Neural Network: **1**, Multilayer Neural Network: **1**	
Total	49			

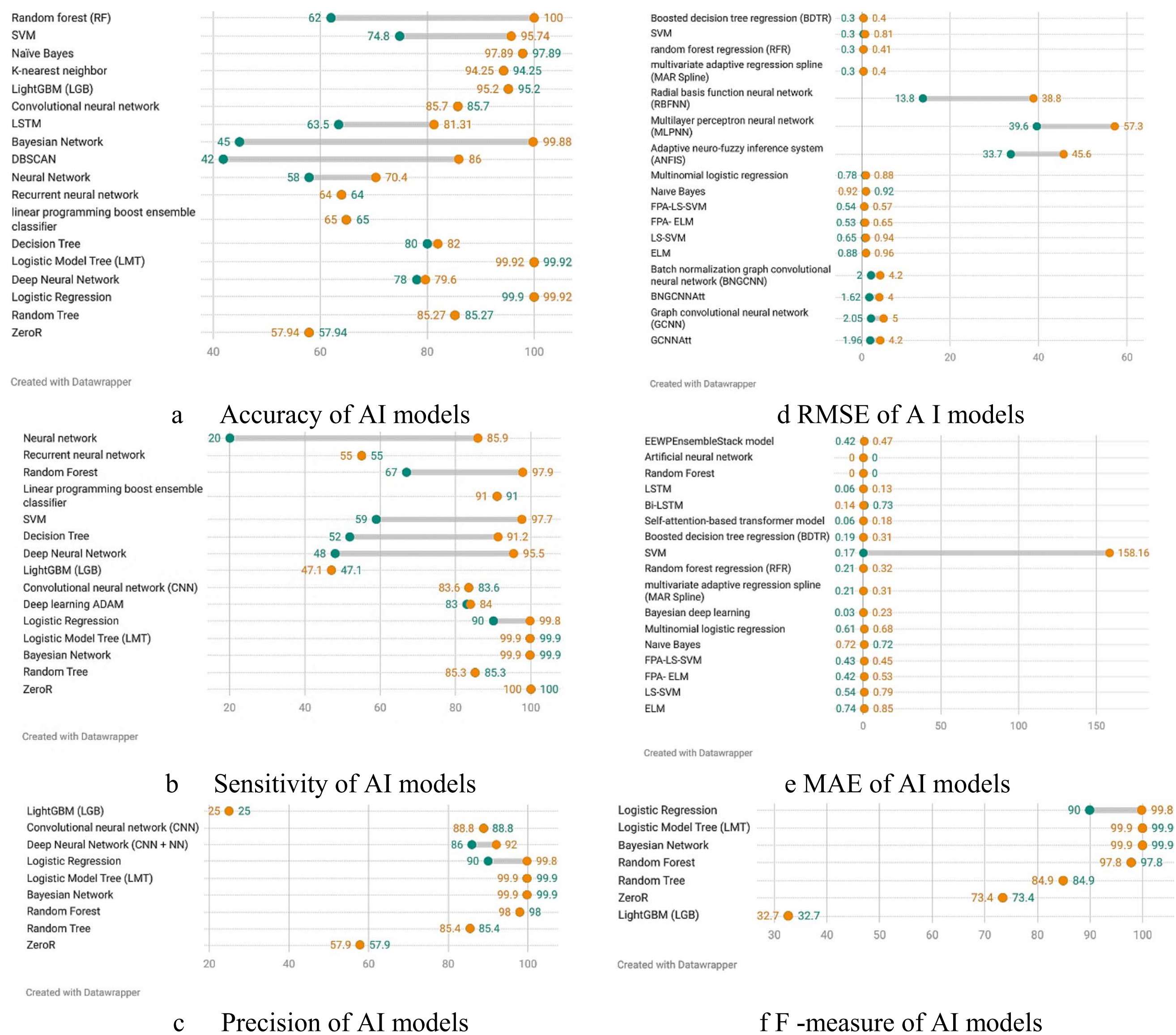


Fig. 7 Comparison of AI model performance

effectiveness. The reliability of the algorithms was characterized by error-expressing criteria (MAE and RMSE), while effectiveness was determined by criteria such as accuracy, precision, recall/ sensitivity, and F-measure. The RF acquired the 100% accuracy (Vasti and Dev 2020) and LR, Logistic Model Tree (LMT) and Bayesian Network (BN) algorithms have achieved 99.92%, 99.92% and 99.88% accuracy, respectively (Debnath et al. 2021). ZeroR obtained a sensitivity value equal to 100%. After it, the LMT, BN, and LR with 99.9%, 99.9%, and 99.8% had most sensitivity values (Debnath et al. 2021). For precision exactly similar to the sensitivity values, the highest values were related to the LMT, BN, and LR algorithms, respectively. Also, same values were obtained for F-measure criteria for LMT, BN, and LR models too (Debnath et al. 2021).

Regarding the MAE indicator, the SVM model has an MAE range of approximately 0.17 to 0.85 (Zhu et al. 2022). However, this range is related to only one of the three studies that reported the MAE for SVM. Due to the large range of MAE in this study, the error values of the other two studies also fall within this range. In the other two studies, the MAE value is in the range of 0.2038 to 0.598 (Marhain et al. 2021; Murwantara et al. 2020). The lowest MAE is related to Random Forest and Artificial Neural Network algorithms, but only in one study, with an approximate value of $10-6$ (Essam et al. 2021). However, in terms of RMSE, the Boosted Decision Tree Regression (BDTR), Multivariate Adaptive Regression Spline (MARS), and Random Forest Regression (RFR) algorithms accessed to lowest value of 0.3 to 0.4 (Marhain et al. 2021).

Discussion

Earthquakes are formidable natural disasters with the potential to cause immense socioeconomic loss and harm to human health. Consequently, providing accurate warnings about the likelihood of large earthquakes can be instrumental in saving lives and minimizing the economic impact. In recent years, the use of AI-based algorithms for earthquake prediction in EEW systems has gained significant traction due to the promising results observed in seismological studies. This systematic review provides a comprehensive summary of AI-based algorithms, encompassing their technical aspects such as predictor variables, target features, and efficiency, with the aim of developing effective EEW systems.

Our findings indicate that the United States, India, and China have been the most prolific publishers of papers related to AI-Based EEWs. As previously mentioned, these countries are situated in some of the most seismically vulnerable regions on Earth (Salam et al. 2021). The presence of the Himalayan seismic belt in India and China (Gupta 2023; Zhang et al. 2022), the circum-Pacific seismic zone in the United States (Zhang et al. 2022), as well as the existence of two major earthquake belts in China (Circum-Pacific and Eurasian belts) (Han et al. 2022), have contributed to a history of frequent and significant earthquakes in these countries. Additionally, due to their substantial populations and high urbanization rates, these countries are particularly susceptible to high mortality rates resulting from earthquakes (He et al. 2021; Mahtta et al. 2022; Seto et al. 2011). Therefore, their keen interest in developing more accurate EEW systems is well-founded. It is worth noting that only one study included in our review focused on earthquake-prone areas outside of these countries, such as Japan, Turkey, Iran, Italy, and Indonesia. Considering the gravity of the earthquake disaster situation in these countries (Veroutsos 2022), we encourage researchers from these regions to undertake further studies in the development of AI-based EEWs.

The researchers predominantly relied on seismic wave characteristics and seismic activity data as input parameters for earthquake forecasting. While historical data from earthquake catalogs provided one category of features, it is worth noting that natural precursors of earthquakes in the event environment constitute another important feature category (Al Banna et al. 2020). In order to enhance the accuracy of future earthquake forecasting, it is advisable for researchers to give due consideration to environmental factors alongside earthquake catalog features. This holistic approach has the potential to yield more precise predictions and improve our understanding of earthquake dynamics.

The primary objective of EEW systems is to predict earthquakes (Cochran et al. 2018). In earthquake prediction, four key components are considered: location, time, magnitude, and occurrence probability (Allen 1976). However, based on the findings, the prediction of earthquake magnitude received more attention compared to other elements. Consequently, there is a pressing need to shift focus towards achieving more precise predictions for the location and timing of earthquakes in future EEW systems. Enhancing our ability to accurately forecast these crucial aspects will greatly contribute to effective earthquake preparedness and response measures.

In terms of algorithm performance, the Random Forest (RF) algorithm achieved remarkable results, with 100% accuracy in earthquake prediction and zero error according to the Mean Absolute Error (MAE) metric. However, it is important to be cautious about the potential overfitting issue associated with such high accuracy (Bejani and Ghatee 2021; Roelofs et al. 2019). RF, as a regression tree method, leverages techniques like bootstrap aggregation and variable randomization to yield excellent outcomes. Its flexibility makes it suitable for addressing large-scale problems (Biau and Scornet 2016; Rigatti 2017).

On the other hand, Logistic Regression (LR), Bayesian Networks (BN), and Logistic Model Trees (LMT) ranked second in terms of sensitivity metric and demonstrated higher precision and F-measure values. These results are consistent with similar reviews that have compared the performance of shallow machine learning algorithms with deep learning algorithms (Al Banna et al. 2020; Mignan and Broccardo 2020). It is worth noting that parameter sensitivity poses a significant challenge for AI algorithms, particularly when working with complex experimental data like seismological datasets (Jiao and Alavi 2020).

The format and collection area of the dataset play a crucial role in obtaining an appropriate dataset for earthquake prediction. Heterogeneous feature distributions and environmental noise can vary in datasets collected from different seismic stations that employ various instruments for data recording (Galkina and Grafeeva 2019; Mousavi et al. 2019b; Zhao et al. 2023). Therefore, the utilization of benchmarking datasets in comparing the performance of different AI algorithms can be instrumental in establishing a standardized evaluation framework. By doing so, we can effectively assess and compare the effectiveness of various AI algorithms in earthquake prediction.

Certain issues arise when working with time-series datasets to train ML algorithms for developing EEW Systems, as evidenced by the fact that such longitudinal data structures comprised the predominant dataset types examined across the literature under review (Galasso et al. 2023). Upon examining the studies incorporated within the review, it was noted that the majority of the literature (Bilal et al. 2022b; Chelidze et al. 2020; Chiang et al. 2022) had addressed this issue by opting not to employ the multi-fold cross-validation technique and the predominant metrics employed centered around RMSE, precision, recall, and ROC-based evaluations to gauge predictive performance.

The Neural Networks (NN) family of algorithms emerged as the most frequently employed AI algorithms in earthquake prediction. Our findings also revealed that a multitude of factors are considered as input variables for earthquake prediction. Developing EEWs typically involves working with large datasets, and the features of NNs, such as adaptive learning, fault tolerance, self-organization, real-time response, high parallelism, flexibility, and strong generalization capabilities, make them well-suited for addressing complex problems like earthquake prediction that involve large volumes of data (Rajasekaran and Pai 2017; Thakur and Konde 2021). Additionally, NNs serve as the foundation for deep learning algorithms, including Long Short-Term Memory (LSTM) networks (Dike et al. 2018; Patterson and Gibson 2017), owing to their unsupervised learning nature.

Despite efforts by scientists to create benchmark datasets specifically tailored for earthquake prediction using AI algorithms (Mousavi et al. 2019a; Zhao et al. 2023), many researchers still face challenges in accessing high-quality labeled benchmark datasets for their specific areas of interest area (Galkina and Grafeeva 2019; Joshi et al. 2022; Vasti and Dev 2020). Consequently, these factors have led to increased attention towards using unsupervised algorithms, particularly for real-time earthquake prediction. However, most of the studies included in our review focused on developing traditional machine learning (ML) algorithms for earthquake prediction. This aligns with the results of studies conducted by Mignan and Broccardo (Mignan and Broccardo 2020) and Al Banna et al. (Al Banna et al. 2020). The preference for using shallow ML algorithms may be attributed to the fact that many of the reviewed studies relied on previous earthquake catalog data, which has a structured data format. To effectively analyze and extract insights from such data, scientists have opted to utilize classical ML models (Mignan and Broccardo 2020). Similarly, in line with the study conducted by Jiao et al. (Jiao and Alavi 2020), our results demonstrate a predominant application of supervised algorithms for earthquake prediction. However, it is anticipated that in the future, unsupervised and data-driven models will also find increased utilization in exploring seismological data.

Despite our diligent efforts to ensure a consistent research process, there are certain limitations to this study that may restrict the generalizability of the results. One limitation pertains to our criteria for excluding non-English articles, which could introduce potential language bias. Additionally, our focus was primarily on studies that developed AI-based models for predicting earthquake magnitude, rather than considering other earthquake features. Including papers that concentrate on predicting other aspects of earthquakes could have resulted in more comprehensive findings.

Furthermore, the comparison of AI models in our review was based on studies that utilized different dataset sources from various regions, each with its own unique seismic characteristics. This variability in dataset sources may influence the performance and outcomes of different AI methods. Consequently, a more reliable assessment of AI performance in EEW systems can be achieved by comparing methods using standardized benchmarking datasets. Such standardized datasets would provide a common basis for evaluating and comparing the effectiveness of different AI models.

Conclusion

Earthquakes, as highly destructive natural disasters, have significant societal implications resulting in human and financial losses. In order to develop reliable EEW systems for earthquake prediction, substantial efforts have been made. This research systematically reviewed EEWs based on AI techniques, considering the growing trend of utilizing AI methods for earthquake prediction. Our findings revealed that the majority of EEWs primarily focused on predicting the magnitude and depths of earthquakes. The predictor parameters were categorized into eight distinct categories, with seismic wave characteristics and seismic activity data being commonly employed for magnitude prediction.

Among the AI algorithms assessed, LR (Logistic Regression), LMT (Logistic Model Trees), and BN (Bayesian Networks) demonstrated the highest accuracy for developing EEW systems. However, it is worth noting that models belonging to the neural network (NN) family, such as artificial neural networks (ANNs), were more prevalent among scientists for earthquake prediction. Considering the voluminous and region-specific nature of seismic data, we recommend researchers to explore data-driven and unsupervised methods in the development of EEW systems. Furthermore, focusing on predicting other crucial components of earthquake events, such as the occurrence time, and incorporating additional input parameters that can contribute to earthquake prediction can enhance the accuracy and comprehensiveness of forecasting.

This comprehensive review offers valuable insights for seismologists and researchers interested in leveraging AI techniques for the development of EEW systems. By considering the suggestions and findings presented herein, advancements can be made in effectively predicting earthquakes and providing more precise and comprehensive information for mitigating their impact.

Appendix

Table 5 Characteristics of the included studies

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
Vasti M (Vasti and Dev 2020), 2020, India\ India	To provide the interested learner with the implementation of the classification algorithms on the real-world earthquake dataset.	(1) Depth (2) Magnitude	1575	Earthquake level	RF	Accuracy	1
						Misclassification error	0
					SVM	Accuracy	0.957
						Misclassification error	0.043
					KNN	Accuracy	0.943
						Misclassification error	0.057
					NB	Accuracy	0.979
						Misclassification error	0.021
Joshi A (Joshi et al. 2022), 2022, India\ Japan	To explore the learning ability of the ensemble model for estimating magnitude based on selected features carefully extracted from the early 3 s of the P phase of the earthquake record.	(1) Period (τc) (2) Predominant period (τp) (3) Velocity squared integral (IV2) (4) Peak ground displacement (Pd) (5) Displacement squared integral (ID2) (6) Ratio of peak ground velocity with peak ground displacements (Tvd) (7) The ratio of the parameter of the autocorrelation function (ACF) at three lags with zero lag (ACF1) 8. The ratio of the area on the positive and negative sides of the abscissa obtained from the displacement function (ACF2)	2951	Magnitude	The EEWPEnsembleStack model (incorporates models like AdaBoost, XGBoost, LightGBM regressor, DT, and Lasso regression, respectively)	R2	0.63
						MAE	0.419
Essam Y (Essam et al. 2021), 2021, Malaysia\ Malaysia	To predict ground motion parameters by artificial neural network (ANN) models as a tool, namely earthquake acceleration, depth, and velocity, in Terengganu.	(1) Acceleration (2) Depth (3) Velocity	Channel HNE: 899.99 s, Channel HNZ: 479.89 s, Time interval of 0.01s for both channels	Acceleration	ANN HNE and HNZ levels	Regression	[0.924,0.939]
						NSE	[0.854,0.881]
						MSE	~10^−11
						MAE	~10^−6

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
				Depth	ANN HNE and HNZ levels	Regression	[0.998,0.999]
						NSE	[0.996,0.999]
						MSE	~10^-12
						MAE	~10^-6
				Velocity	ANN HNE and HNZ levels	Regression	[0.996,0.997]
						NSE	[0.992,0.993]
						MSE	~10^−10
						MAE	~10^−6
				Acceleration	RF HNE and HNZ levels	Regression	[0.689,0.726]
						NSE	[0.346,0.361]
						MSE	~10^−12
						MAE	~10^−6
				Depth	RF HNE and HNZ levels	Regression	[0.994,0.995]
						NSE	[0.983,0.985]
						MSE	~10^−12
						MAE	~10^−6
				Velocity	RF HNE and HNZ levels	Regression	[0.993,0.994]
						NSE	[0.979,0.985]
						MSE	~10^−12
						MAE	~10^−6
Sadhukhan B (Sadhukhan et al. 2023), 2023, India\ Various countries	To use deep learning techniques to predict the magnitude of an impending earthquake	(1) Time elapsed (T) for the last "n" seismic events (2) The Mean Magnitude (Mmean) (3) The slope of the Gutenberg-Richter curve (b – value) (4) y-intercept of the Gutenberg-Richter curve (a value) (5) Magnitude defcit (ΔM) (6) Rate of the square root of the seismic energy (dE1/2) (7) Sum of mean square deviations from Regression line using the Gutenberg-Richter inverse power law (8) Mean time between characteristic events (μ)	107,215	Magnitude	LSTM	MAE	[0.061,0.128]
						MSE	[0.006,0.017]
						log-cosh loss	[0.042,0.18]
						MSLE	[0.003,0.044]
					Bi-LSTM	MAE	[0.073,0.142]
						MSE	[0.01,0.019]
						log-cosh loss	[0.016,0.123]
						MSLE	[0.008,0.022]
					Self-attention-based transformer model	MAE	[0.062,0.181]
						MSE	[0.006,0.018]
						log-cosh loss	[0.043,0.126]
						MSLE	[0.003,0.026]

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
Marhain S (Marhain et al. 2021), 2021, Malaysia\ Malaysia	To use multiple algorithm model for earthquake prediction in Terengganu.	(1) Acceleration (2) Depth	Not mentioned	Acceleration	BDTR HNE and HNZ datasets	RMSE	[0.306,0.401]
						MAE	[0.187,0.305]
						R	[0.626,0.652]
						WI	[0.384,0.771]
					SVM:Type2 HNE and HNZ datasets	RMSE	[0.341,0.413]
						MAE	[0.269,0.329]
						R	[0.51,0.564]
					SVM:Type1 HNE and HNZ datasets	RMSE	[0.342,0.406]
						MAE	[0.269,0.298]
						R	[0.455,0.57]
					RFR HNE and HNZ datasets	RMSE	[0.365,0.41]
						MAE	[0.245,0.321]
						R	[0.327,0.522]
					MARS HNE and HNZ datasets	RMSE	[0.323,0.397]
						MAE	[0.238,0.31]
						R	[0.471,0.536]
				Depth	BDTR HNE and HNZ datasets	RMSE	[0.302,0.376]
						MAE	[0.218,0.282]
						R	[0.591,0.732]
						WI	[0.448,0.917]
					SVM:Type2 HNE and HNZ datasets	RMSE	[0.299,0.34]
						MAE	[0.275,158.16]
						R	[0.359,0.438]
					SVM:Type1 HNE and HNZ datasets	RMSE	[0.303,0.373]
						MAE	[0.204,0.298]
						R	[0.36,0.437]

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
					RFR HNE and HNZ datasets	RMSE	[0.3,0.342]
						MAE	[0.205,0.262]
						R	[0.448,0.467]
					MARS HNE and HNZ datasets	RMSE	[0.3,0.337]
						MAE	[0.205,0.254]
						R	[0.307,0.32]
Kaftan I (Kaftan et al. 2017), 2017, Turkey\ Turkey	Two different ANNs (which are MLPNN and RBFNN) and ANFIS were applied to the earthquake frequency data from Western Turkey to predict possible earthquake frequencies	Consecutive monthly frequency data up to six consecutives data values	408	Earthquake frequencies	RBFNN	R	[0.3,0.93]
						RMSE	[13.8,38.8]
					MLPNN	R	[0.18,0.38]
						RMSE	[39.6,57.3]
					ANFIS	R	[0.17,0.44]
						RMSE	[33.7,45.6]
Kilb D (Kilb et al. 2021), 2021, USA\ USA	To test the Propagation of Local Undamped Motion (PLUM) EEW algorithm and finding optimal IMMI trigger thresholds for detecting M5 + earthquakes within the West Coast states of California, Oregon, and Washington.	(1) Velocity (2) Acceleration	1. A historical catalog of 558 M3.5 + earthquakes 2. 102 signals between 1999 and 2015	Earthquake frequencies (Magnitude, time)	PLUM earthquake early warning (EEW) algorithm	False Detections	0
						Mean detection times (second)	8
						Median detection times (second)	6
						For the older 1999–2015 earthquakes mean detection times (second)	11
						For the older 1999–2015 earthquakes median detection times (second)	6
						Correctly detected earthquakes with M5+	[0.33,1.0]
						Correctly detected earthquakes with M < 5	[0.0,0.64]
						Avoid non-local earthquake (Anomalous and Teleseismic) signals	1

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
Liu et al. (2022), 2022 China\ China	To use the PCA method for extracting features from origin data, and to predict the earthquake using a machine learning method LightGBM (LGB).	Ultra-low frequency electromagnetic anomalies (acoustic and magnetic signals)	678	Magnitude	LGB (a kind of implementation of GBDT)	Accuracy	0.522
						Precision	0.25
						Recall	0.471
						F-measure	0.327
Mousavi SM (Mousavi et al. 2019a), 2019 USA\ Various countries	To use a multitask temporal convolutional neural network to learn epicentral distance and P travel time from 1-min seismograms	Earthquake signals (P-wave, S-wave)	150,000	Location, Time, Depth	Bayesian Convolutional Neural Network	MAE for distance	0.23 (km)
						MAE for Time	0.03 (s)
						Mean Error for epicenter prediction	7.3 (km)
						Mean Error for origin time	0.4 (s)
						Mean Error for depth	6.7 (km)
Murwantara IM (Murwantara et al. 2020), 2019 Indonesia\ Various countries	To estimate a medium to-long term prediction via machine learning algorithms and compares their performance	(1) Date (2) Time (3) Latitude (4) Longitude (5) Magnitude (6) Depth	Not mentioned (375 gigabytes)	Location, Depth and Magnitude	SVM	RMSE: 30 years and grouping data based on magnitude	0.751
						MAE: 30 years and grouping data based on magnitude	0.598
						MAPE: 30 years and grouping data based on magnitude	0.156
						MSE: 30 years and grouping data based on magnitude	0.564
						RMSE: 10 years and not grouping data based on magnitude	0.805
						MAE: 10 years and not grouping data based on magnitude	0.618
						MAPE: 10 years and not grouping data based on magnitude	0.135

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
						MSE: 10 years and not grouping data based on magnitude	0.648
					MLR	RMSE: 30 years and grouping data based on magnitude	0.777
						MAE: 30 years and grouping data based on magnitude	0.614
						MAPE: 30 years and grouping data based on magnitude	0.16
						MSE: 30 years and grouping data based on magnitude	0.604
						RMSE: 10 years and not grouping data based on magnitude	0.884
						MAE: 10 years and not grouping data based on magnitude	0.678
						MAPE: 10 years and not grouping data based on magnitude	0.15
						MSE: 10 years and not grouping data based on magnitude	0.782
					NB	RMSE: 30 years and grouping data based on magnitude	0.922
						MAE: 30 years and grouping data based on magnitude	0.716
						MAPE: 30 years and grouping data based on magnitude	0.183
						MSE: 30 years and grouping data based on magnitude	0.851

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
Salam MA (Salam et al. 2021), 2021, Egypt\ USA	To predict the earthquake magnitude during fifteen days using two hybrid machine learning models	(1) Time during the range of n events (T) (2) Average magnitude of the last n events of the period (M_mean) (3) Square root of released seismic energy during time T (DE^(1/2)) (4) b_value, the slope of the curve between the log of frequency of occurred earthquakes and the earthquake magnitude given from Richter inverse power law (5) η value, sum of mean square deviation based on inverse power law (6) ΔM, magnitude deficit- the difference between the observed magnitude and the expected one (7) μ, meantime among the characteristic events	693 time period	Magnitude	FPA-LS-SVM	RMSE	[0.537,0.565]
						MAE	[0.429,0.447]
						SMAPE	[0.035,0.097]
						PMRE	[19.479,20.932]
					FPA- ELM	RMSE	[0.529,0.646]
						MAE	[0.418,0.525]
						SMAPE	[0.03,0.096]
						PMRE	[21.131,25.128]
					LS-SVM	RMSE	[0.651,0.936]
						MAE	[0.538,0.789]
						SMAPE	[0.022,0.083]
						PMRE	[28.381,40.84]
					ELM	RMSE	[0.881,0.962]
						MAE	[0.738,0.845]
						SMAPE	[0.023,0.066]
						PMRE	[38.077,45.681]
Samui P (Samui and Kim 2014), 2014, India\ Various countries	To predict the magnitude (M) of induced earthquakes based on reservoir parameters	(1) Reservior depth (H) (2) Comprehensive parameter (E)	Not mentioned	Magnitude	RVM	R	0.933
						VAF	83.96
						Error Rate	~0.1
					LSVM	R	0.903
						VAF	82.08
						Error Rate	~0.2
					Linear Regression	Error Rate	~0.8
					ANN	Error Rate	~0.6

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
Thomas AM (Thomas et al. 2021), 2021, USA\USA	To detect LFEs on the deep extension of the San Andreas fault (SAF) using several variations of a U-Net, a type of convolutional neural network (CNN)	(1) S-Wave (2) P-Wave	1.73 million waveforms	Low-Frequency Earthquakes (S-wave arrival times)	CNN	Accuracy	0.857
						Precision	0.888
						Recall	0.836
Wang Q (Wang et al. 2020), 2017, USA\USA	To learn the spatiotemporal relationship among earthquakes in different locations and make predictions by taking advantage of that relationship	(1) Latitude (2) Longitude (3) Time (4) Depth 5- Magnitude 6. Earthquake presence	Case study 1: 120 Case study 2: 600	The number of earthquakes	LSTM networks	Accuracy	[0.635,0.813]
						TP accuracy	[0.468,0.748]
						TN accuracy	[0.686,0.796]
Zhang X (Zhang et al. 2021), 2021, China\Italy	Designed a multi-branch FCN for real-time EEW.	(1) Magnitude (2) Depth (3) Time (4) Length (5) Width	1273	Epicenter	FCN	Mean epicenter error(km)	~[6.0,10.0]
						Mean depth error(km)	~[1.4,1.8]
				Depth			
				Magnitude			
						Mean magnitude error	~[0.25,0.35]
Zhu J (Zhu et al. 2022), 2022, China\Japan	To determine earthquake magnitudes using a machine-learning method comprising multiple parameter inputs, namely, the support vector machine magnitude estimation (SVM-M) model	(1) Peak displacement (Pd) (2) peak velocity (Pv) (3) peak acceleration (Pa) (4) P-wave arrival time (5) Average period (τc) (6) Product parameter (TP) (7) Peak ratio (Tva) (8) P-wave index value (PIv) (9) Velocity squared integral (IV2) (10) Cumulative absolute velocity (CAV) 11. Cumulative vertical absolute displacement(cvad) 12. Cumulative vertical absolute velocity(cvav) 13. Cumulative vertical absolute acceleration (cvaa)	1883	Magnitude	SVM magnitude estimation (SVM-M) model	Standard deviations of the magnitude estimation errors	~[0.24,0.4]
						MAE ($3 \leq MJMA < 6.5$)	~[0.18,0.31]
						MAE ($6.5 \leq MJMA \leq 7.2$)	~[0.17,0.85]
						Percentages of the Predicted Magnitudes in Absolute Error Range of $0 \leq \omega < 0.6$	95.48
						Percentages of the Predicted Magnitudes in Absolute Error Range of $0.6 \leq \omega < 1.2$	4.36
						Percentages of the Predicted Magnitudes in Absolute Error Range of $1.2 \leq \omega$	0.16

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
Zuccolo E (Zuccolo et al. 2021), 2021, Italy\ European countries (Italy, France, Iceland, Greece, Romania, and the Netherlands)	To Compare the operational performance of two popular regional EEW algorithms, PRobabilistic and Evolutionary early warning SysTem (PRESTo), and the implementation of the Virtual Seismologist magnitude component within SeisComP, VS(SC)	(1) Focal mechanisms (based on average strike, dip, and rake values) (2) Magnitudes (3) Hypocentral depths (4) Seismic network densities/configurations (5) Velocity models (6) Peak Ground Acceleration (PGA)	27	Epicenter, Depth, Magnitude, Peak Ground Acceleration (PGA)	PRESTo EEW (FilterPicker algorithm)	Mean Error {First estimate, Stable estimate} (km)	[3.51,11.0]
						Median Error {First estimate, Stable estimate} (km)	[2.05,7.97]
						Mean Error {First estimate, Stable estimate} (km)	[-13.10,0.01]
						Median Error {First estimate, Stable estimate} (km)	[-5.54,-0.59]
						Mean Error {First estimate, Stable estimate}	[-0.46,0.13]
						Median Error {First estimate, Stable estimate}	[-0.32,0.20]
						Prediction accuracy; average MD: {15 s, 10 s, 5s}	[0.45,0.82]
					VS(SC) EEW (DBSCAN)	Mean Error {First estimate, Stable estimate} (km)	[3.02,8.68]
						Median Error {First estimate, Stable estimate} (km)	[1.75,2.48]
						Mean Error {First estimate, Stable estimate} (km)	[-6.29,-0.23]
						Median Error {First estimate, Stable estimate} (km)	[-1.72,-0.83]
						Mean Error {First estimate, Stable estimate}	[-0.55,0.03]
						Median Error {First estimate, Stable estimate}	[-0.49,0.01]
						Prediction accuracy; average MD: {15 s, 10 s, 5s}	[0.42,0.86]

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
Asim KM (Asim et al. 2017), 2017, Pakistan\Pakistan	Earthquake magnitude prediction for Hindukush region.	(1) Time (2) The mean magnitude of the last n events (3) The rate of square root of seismic energy release (4) b value: the slope of the curve between earthquake magnitudes and the log of frequency of earthquakes (5) Deviation of actual data from the Gutenberg–Richter inverse power law (6) The difference between the maximum observed and the maximum occurred earthquake magnitude (7) Seismicity precursor: Mean time between characteristic events (l) among the last n events (8) Deviation from Mean time between characteristic events	441	Earthquake occurrence with magnitude > = 5.5 over a time span of one month	Neural Network	TP	22
						FP	9
						TN	55
						FN	46
						Sensitivity	0.32
						Specificity	0.86
						PPV	0.71
						NPV	0.54
						Accuracy	0.58
					Recurrent Neural Network	TP	37
						FP	17
						TN	48
						FN	30
						Sensitivity	0.55
						Specificity	0.74
						PPV	0.68
						NPV	0.62
						Accuracy	0.64
					RF	TP	46
						FP	27
						TN	36
						FN	23
						Sensitivity	0.67
						Specificity	0.57
						PPV	0.63
						NPV	0.61
						Accuracy	0.62

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
					Linear Programming Boost Ensemble Classifier	TP	63
						FP	40
						TN	23
						FN	6
						Sensitivity	0.91
						Specificity	0.36
						PPV	0.61
						NPV	0.79
						Accuracy	0.65
Berhich A (Berhich et al. 2021), 2021, Morocco\ Morocco	Spatiotemporal earthquake prediction by giving the four parameters as outputs: Magnitude, location, time, and accuracy of the prediction	(1) Magnitude distribution (2) Source depth (3) Earthquake location (4) Date and time	32,396	Earthquake spatiotemporal magnitude	LSTM model	MAE	0.031
					Multi-layer NN	MAE	0.074
Yousefzadeh M (Yousefzadeh et al. 2021), 2021, Iran\ Iran	To investigate the effect of spatial parameters on four ML algorithms' performance for predicting the magnitude of future earthquakes in Iran	(1) Latitude (2) Longitude (3) Depth (4) 16 seismic parameters based on b value, (5) FD parameter (Calculated Kernel Density Estimation (KDE) for the study area in each cell)	1564	Magnitude	SNN	Accuracy	[0.612,0.704]
						Sensitivity	[0.2,0.859]
					SVM	Accuracy	[0.748,0.78]
						Sensitivity	[0.59,0.977]
					DT	Accuracy	[0.8,0.82]
						Sensitivity	[0.52,0.912]
					DNN	Accuracy	[0.78,0.796]
						Sensitivity	[0.48,0.955]
Bilal MA (Bilal et al. 2022a), 2022, China\California (USA)	To early prediction of an earthquake using a deep learning-based model BNGCNN model	(1) Magnitude (2) Depth (3) Location (4) Three-component waveforms (P wave, S wave, Surface wave)	1477	Latitude	BNGCNN	Error	~[-0.5, +0.5]
				Longitude		Error	~[-0.5, +0.5]
				Depth		Error	~[-20, +15]
				Magnitude		Error	~[-0.5, +0.3]
				Latitude	GNN	Error	~[-0.5, +0.5]
				Longitude		Error	~[-0.5, +0.5]
				Depth		Error	~[-16, +15]
				Magnitude		Error	~[-0.5, +0.5]

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
Bilal MA (Bilal et al. 2022b), 2022, China\ Alaska and Japan	To early prediction of earthquake magnitude and depth using a graph convolutional neural network with batch normalization and attention mechanisms	(1) Magnitude (2) Three-component waveforms (P wave, S wave, Surface wave (3) Depth	4931	Depth Magnitude	BNGCNNAtt	RMSE for depth RMSE for magnitude	[1.62,2.87] ~[2.9,4.0]
					BNGCNN	RMSE for depth RMSE for magnitude	~[2.0,3.14] ~[3.85,4.2]
					GCNNAtt	RMSE for depth RMSE for magnitude	~[1.96,3.1] ~[3.8,4.2]
					GCNN	RMSE for depth RMSE for magnitude	~[2.05,3.18] ~[3.8,5.0]
Chelidze T (Chelidze et al. 2020), 2020, Georgia\ Georgia	To develop a physical model of seismic activity	(1) Water level in wells (2) Tidal variations (3) Local magnetic field components (4) Hourly geomagnetic DST index	365	Earthquake occurrence with magnitude of M3-4	ADAM	ROC Recall	[0.81,0.97] [0.83,0.84]
Chiang YJ (Chiang et al. 2022), 2021, Taiwan\ Taiwan	To predict the greatest earthquake ground motion early using methods based on artificial intelligence, when the P-wave arrives at seismograph stations	P-wave time window	8620 acceleration records	Peak ground acceleration (PGA) exceeds a pre-defined probability or not.	DNN	Precision Recall F1-score	[0.86,0.92] [0.8,0.9] [0.83,0.91]
Debnath P (Debnath et al. 2021), 2021, India\India	To develop a method for forecasting the earthquake magnitude range of earthquakes using machine learning classifier algorithms.	(1) Time (2) Latitude (3) Longitude (4) Depth (5) Number of Seismic stations (6) Seismic gap (7) Horizontal distance between epicenter and station (8) Root mean square of the travel time residual (RMS) (9) Updated time of earthquake (10) Type of Seismic Event/ Network that reported location of earthquake 11. Network that reported magnitude of earthquake 12. Horizontal error 13. Depth error 14. Magnitude error 15. Earthquake magnitude	26,978	Magnitude	Simple Logistic	Precision	0.998

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
						Recall	0.998
						Accuracy	0.999
						F-Measure	0.998
						MCC	0.997
						Kappa Statistic	0.998
					LMT	Precision	0.999
						Recall	0.999
						Accuracy	0.999
						F-Measure	0.999
						MCC	0.999
						Kappa Statistic	0.998
					Bayes Net	Precision	0.999
						Recall	0.999
						Accuracy	0.999
						F-Measure	0.999
						MCC	0.998
						Kappa Statistic	0.998
					RF	Precision	0.98
						Recall	0.979
						Accuracy	0.979
						F-Measure	0.978
						MCC	0.969
						Kappa Statistic	0.96
					Random Tree	Precision	0.854
						Recall	0.853
						Accuracy	0.853
						F-Measure	0.849
						MCC	0.717
						Kappa Statistic	0.706
					ZeroR	Precision	0.579
						Recall	1
						Accuracy	0.579
						F-Measure	0.734
						MCC	0.43
						Kappa Statistic	0.24

Table 5 (continued)

Author, Year, First author country/Study region	Aim of study	Predictors	Dataset size	Target Features	AI Model	Performance index name	Performance value (unit)
					Logistic Regression	Precision	0.9
						Recall	0.9
						Accuracy	0.999
						F-Measure	0.9
						MCC	0.997
						Kappa Statistic	0.996
Feng H (Feng et al. 2022), 2022, China\ China	To explore the uncertainty of machine learning based on the assessment of model performance	(1) Peak ground acceleration (2) Distance from fault (3) Earthquake intensity (4) Lithology (5) Elevation (6) Slope (7) Aspect (flat; north; northeast; east; southeast; south; southwest; west; northwest) (8) Curvature (9) Soil type (10) Distance from the road 11. Distance from the river 12. Topographic wetness index 13. Land use type (cultivated land; forest land; grass; waters)	1404	Landslide Prediction	RF	ROC	0.9
					SVM	ROC	0.8
					Logistic Regression	ROC	0.74
					ANN	ROC	0.72

R2 R square, *MAE* Mean absolute error, *NSE* Nash Sutcliffe Efficiency, *MSE* Mean Squared Error, *MSL* EMean Squared Logarithmic Error, *RMSE* Root Mean Square Error, *R* Coefficient of Correlation, *WI* Wilmott Index, *MAPE* Mean absolute percentage error, *SMAPE* Symmetric Mean Absolute Percentage Error, *PMRE* Percent Mean Relative Error, *VAF* Variance Accounted for, *MJMA* Japan Meteorological Agency magnitude scale, *TP* True Positive, *FP* False Positive, *TN* True Negative, *FN* False Negative, *PPV* Positive predictive value, *NPV* Negative predictive value, *ROC* Receiver operating characteristic, *MCC* Matthews R, *RF* Random Forest, *RFR* Random Forest Regression, *SVM* Support vector machine, *KNN* K-nearest neighbor, *NB* Naïve Bayes, *DT* Decision Tree, *ANN* Artificial Neural Network, *DNN* Deep Neural Network, *CNN* Convolutional Neural Network, *FCN* Fully Convolutional Network, *SNN* Spiking neural network, *LSTM* Long Short-Term Memory, *Bi-LSTM* Bi-directional Long Short-Term Memory, *BDTR* Boosted Decision Tree Regression, *MARS* Multivariate Adaptive Regression Spline, *RBFNN* Radial Basis Function Neural Network, *MLPNN* Multilayer Perceptron Neural Network, *ANFIS* Adaptive Neuro-Fuzzy Inference System, *PLUM* Propagation of Local Undamped Motion, *LGB* LightGBM, *GBDT* Gradient Boosting Decision Tree, *MLR* Multinomial Logistic Regression, *LSVM* Linear Support Vector Machine, *LS-SVM* Least Square Support Vector Machine, *FPA-LS-SVM* Flower Pollination Algorithm Least Square Support Vector Machine, *ELM* Extreme Learning Machine, *FPA-ELM* Flower Pollination Algorithm Extreme Learning Machine, *RVM* Relevance Vector Machine, *DBSCAN* Density-Based Spatial Clustering of Applications with Noise, *GCNN* Graph Convolutional Neural Network, *BNGCNN* Batch Normalization Graph Convolutional Neural Network, *BNGCNNatt* Batch Normalized Graph Convolutional Neural Network with Attention Mechanism, *GCNNatt* Graph Convolutional Neural Network with Attention Mechanism, *GNN* Graph Neural Networks, *LMT* Logistic Model Tree

Author contributions Seyed Mohammad Ayyoubzadeh conceptualized the research. Pirhossein Kolivand, Sharareh Rostam Niakan Kalhori and Peyman Saberian supervised the manuscript. Mozhgan Tanhapour, Fereshteh Karimi, Zohreh Javanmard, Soroush Heydari, Seyed Saeid Hoseini Talari, Seyed Mohsen Laal Mousavi, and Maryam Alidadi wrote the original draft. Mahnaz Ahmadi reviewed the manuscript.

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Declarations

Competing interests The authors declare no competing interests.

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