Artificial Intelligence in Geosciences 5 (2024) 100075

Contents lists available at ScienceDirect

Artificial Intelligence in Geosciences

journal homepage: www.keaipublishing.com/en/journals/artificial-intelligence-in-geosciences

The role of artificial intelligence and IoT in prediction of earthquakes: Review

Joshua Pwavodi [a,*], Abdullahi Umar Ibrahim [b,c,**], Pwadubashiyi Coston Pwavodi [d], Fadi Al-Turjman [b,e,f], Ali Mohand-Said [a]

[a] Ecole et Observatoire des Sciences de La Terre, ITES UMR7063 – CNRS/Universit'e de Strasbourg, 5 rue Rene Descartes, 67084, Strasbourg, France
[b] Research Center for Science, Technology and Engineering (BILTEM), Near East University, 99138, Nicosia, TRNC, Mersin 10, Turkey
[c] Department of Biomedical Engineering, Near East University, Mersin 10, Nicosia, 99010, Turkey
[d] Department of Biomedical Engineering, Faculty of Engineering, Cyprus International University, Haspolat, North Cyprus via Mersin 10, Nicosia, 99258, Turkey
[e] Artificial Intelligence Engineering Department, AI and Robotics Institute, Near East University, Mersin, 99138, Turkey
[f] Research Center for AI and IoT, Faculty of Engineering, University of Kyrenia, Mersin 99138, Turkey

ARTICLE INFO

Keywords:
Earthquakes
Seismicity
Artificial intelligence
Internet of things
Prediction

ABSTRACT

Earthquakes are classified as one of the most devastating natural disasters that can have catastrophic effects on the environment, lives, and properties. There has been an increasing interest in the prediction of earthquakes and in gaining a comprehensive understanding of the mechanisms that underlie their generation, yet earthquakes are the least predictable natural disaster. Satellite data, global positioning system, interferometry synthetic aperture radar (InSAR), and seismometers such as microelectromechanical system, seismometers, ocean bottom seismometers, and distributed acoustic sensing systems have all been used to predict earthquakes with a high degree of success. Despite advances in seismic wave recording, storage, and analysis, earthquake time, location, and magnitude prediction remain difficult. On the other hand, new developments in artificial intelligence (AI) and the Internet of Things (IoT) have shown promising potential to deliver more insights and predictions. Thus, this article reviewed the use of AI-driven Models and IoT-based technologies for the prediction of earthquakes, the limitations of current approaches, and open research issues. The review discusses earthquake prediction setbacks due to insufficient data, inconsistencies, diversity of earthquake precursor signals, and the earth's geophysical composition. Finally, this study examines potential approaches or solutions that scientists can employ to address the challenges they face in earthquake prediction. The analysis is based on the successful application of AI and IoT in other fields.

1. Introduction

Earthquakes loom large as major catastrophic events due to their substantial magnitude and the potential to trigger ancillary hazards like landslides, fires, liquefaction, and tsunamis. This multi-faceted nature of seismic events underscores their capacity to wreak havoc, causing significant losses and damages (Hamdy et al., 2022). There has been an increasing interest in the prediction of earthquakes and in gaining a comprehensive understanding of the mechanisms that underlie their generation, yet earthquakes are the least predictable natural disaster (Laasri et al., 2015). Earthquakes occur due to stress and energy release along fault zones, leading to tectonic plates failure, slip and shift (Uyeda and Kanamori, 1979; Pwavodi and Doan, 2024; Pwavodi, 2023). This natural phenomenon negatively impacts the environment, economy, lives, and properties (Allen and Melgar, 2019). Therefore, it has become more important than ever to investigate its nucleation, tectonic fault ruptures, the interaction between slip modes, slow slip events, and fluid-induced earthquakes (Uyeda and Kanamori, 1979; Lay and Kanamori, 1981; Lay et al., 1982; Davis et al., 1983; C. Scholz, 1998; Liu and Rice, 2007; Kodaira et al., 2004; Saffer and Tobin, 2011; Kitajima and Saffer, 2012, Pwavodi and Doan, 2024) and predict its occurrence in terms of time, date, location, and magnitude.

Earthquakes occur primarily in subduction zones, submerged mid-Atlantic ridges, and transform fault zones (Lay, 2016; Ando, 1975; Kanamori, 1972; Storetvedt, 1990). Some of the greatest earthquakes in

* Corresponding author.
** Corresponding author. Research Center for Science, Technology and Engineering (BILTEM), Near East University, 99138, Nicosia, TRNC, Mersin 10, Turkey.
E-mail addresses: pwavodi@unistra.fr (J. Pwavodi), abdullahi.umaribrahim@neu.edu.tr (A.U. Ibrahim).

https://doi.org/10.1016/j.aiig.2024.100075
Received 5 July 2023; Received in revised form 18 February 2024; Accepted 20 February 2024
Available online 27 February 2024

Table of abbreviations

AAP	Adaptive Affinity Propagation
AE	Absolute Error
AFAD	Disaster and Emergency Management Authority
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BD	Big Data
BRB	Belief Rule-Based
CNNs	Convolutional Neural Networks
DAS	distributed acoustic sensing
DL	Deep Learning
DNN	Deep Neural Network
EAF	East Anatolian Transform Fault
EEWS	Early Earthquake Warning System
EWS	Early Warning System
FL	Federated Learning
FP	False Positive
GPS	Global Position System (GPS)
GRU	Gated Recurrent Network
HC	Hierarchical Clustering
HKKH	Hindukush Karakoram Himalayan
HMM	Hidden Markov Model
HVSR	Horizontal to Vertical Spectral Ratio
ICT	Information and Communication Technology
IIoT	Industrial Internet of Things
InSAR	Interferometry Synthetic Aperture Radar
IoMT	Internet of Medical Things
IoNT	Internet of Nano Things
IoT	Internet of Things
IT	Information Technology
KMC	K-means Clustering
KNN	K-Nearest Neighbour
LCL	Log-Cosh Loss
LR	Logistic Regression
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MEMS	Micro-Electromechanical System
ML	Machine Learning
MSE	Mean Square Error
MSLE	Mean Squared Logarithmic Error
NB	Näıve Bayes
NIED	National Research Institute of Earth Science and Disaster Prevention
NN	Neural Networks
OBS	Seismometers, Ocean Bottom Seismometers
PCA	Principal Component Analysis
PKNN	Probabilistic K-Nearest Neighbour
PNN	Probabilistic Neural Network
PPV	Peak Particle Velocity
QBs	Quarry Blasts
QDA	Quadratic Discriminant Analysis
RBFNN	Radial Basis Function Neural Network
RF	Random Forests
RML	Reinforcement Machine Learning
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SCI	Science Citation Index
SCI-EXPANDED	Science Citation Index and Expanded
SML	Supervised Machine Learning
SVM	Support Vector Machine
SVR	Support Vector Regression
TP	True Positive
UML	Unsupervised Machine Learning

history are associated with subduction zones (a convergent plate boundary), such as the Tohoku earthquake, 2011 (M9.1), the Alaska earthquake, 1964 (M9.2), the Chilean earthquake, 1960 (M9.5), the Nankai-do earthquake, 1946 (8.2) and the Tonankai earthquake, 1944 (8.3) (Lay, 2016; Ando, 1975; Kanamori, 1972). Other earthquake occurrences are found on the submerged mid-Atlantic Ridge (a divergent plate boundary) and on the Alpide earthquake belt that extends from Java to Sumatra through the Himalayas, the Mediterranean, and out into the Atlantic. The Indonesia earthquake, 2004 (M9.1) was located on the latter (Storetvedt, 1990).

In 2023 there were several mild and devastating earthquakes that have been recorded around the globe in the areas of Peru, China, Mexico, Hawaii, Philippines, Papua New Guinea, Morocco, Turkiye-Syria etc. For example, the most devastating earthquake of 2023 was the Turkiye-Syria doublet earthquake on February 6th, with the highest magnitude of M7.8 (Dal Zilio and Ampuero, 2023), occurring along the East Anatolian Transform Fault (EAF) (Arpat and Şaroğlu, 1972; 1975) and accompanied by several thousands of aftershocks (Ni et al., 2023). The left-lateral displaced transform fault is about 1200 km long and divides the Arabian and Anatolian plates (Arpat and Şaroğlu, 1972; 1975). This earthquake could be due to a rupture along the fault zone resulting from cumulative energy and stress accumulation. The earthquake has resulted in approximately 56,000 deaths, over 125,000 injuries, over 2 million displaced people, and destroyed more than 200, 000 buildings, according to the Disaster and Emergency Management Authority (AFAD). It is also estimated that damages account for over 100 billion US dollars. Historically, the EAF has hosted several thousands of earthquakes of varying magnitudes.

As the world grapples with the aftermath of past and recent earthquakes, including the tragic Turkiye-Syria doublet earthquake in February 2023 and other parts of the world, the ongoing quest to develop effective earthquake prediction methods remains a paramount focus for scientists worldwide. In the ongoing pursuit of understanding earthquake, scientists have endeavoured to develop approaches that can be used to predict earthquakes. The prediction of earthquakes revolves around three main features: possible date and time, location, and magnitude. Here in this work, we closely look at the three categories of methods that have been used in attempt to predict earthquake (a) Advances using devices like the seismometers, distributed acoustic sensing (DAS), satellite data, global position system (GPS) and InSAR. (b) Advances in artificial intelligence (AI) and machine learning (ML) (c) Internet of Things (IoT-based) devices.

Seismologists, through seismic monitoring devices called seismometers, have been able to detect, record, and analyze the seismic waves produced by earthquakes (Kanamori, 2005; Allen et al., 2009; Allen and Melgar, 2019). Some seismometers types are micro-electromechanical system (MEMS) (Khan and Kwon, 2022), seismometers, ocean bottom seismometers (OBS) (Kamei et al., 2013; Dessa and Kaneda, 2004) and distributed acoustic sensing (DAS) systems (Shan et al., 2017; Fern'andez-Ruiz et al., 2020; Shinohara et al., 2022; Gonzalez-Herraez et al., 2021). Other approaches for monitoring and earthquake prediction are based on the use of satellite data, global position system (GPS) (Mazzotti et al., 2000; Su et al., 2016; Gitis et al., 2021) and InSAR (Didier et al., 1994; Zebker and Goldstein, 1986; Hooper et al., 2012). Despite scientists' efforts, no technique can be used to make accurate predictions of earthquakes (Bhatia et al., 2023; Xin et al., 2022).

However, as scientific exploration intersects with technological innovation, computer science and software engineering have paved the way for ground breaking advancements in artificial intelligence (AI), machine learning (ML), and deep learning (DL). These technologies have shown their efficacy in forecasting or predicting the weather, stock market and the energy industry (Al-Turjman and Alturjman, 2018; Pwavodi et al., 2023). The underlying mechanism of the machine learning algorithms involves training algorithms on existing data with known outcomes, enabling these models to consistently interpret new and unexplored data (Pwavodi et al., 2023). Applying this paradigm to earthquake prediction, AI holds the promise of leveraging past event patterns obtained from measurement instruments to predict future seismic activities based on observations from measurement instruments (Zhou et al., 2017).

The array of AI and ML algorithms employed in earthquake prediction, encompassing ANN, SVM, FL, DL, Bi-LSTM, SABT, ANFIS, SVR, PKNN, NB, HMM, KMC, HC, PNN, CNNs etc., leverages diverse datasets—seismic, satellite, GPS—to train and predict models (Zhou et al. (2020); Gitis et al. (2021); Essam et al. (2021); Xiong et al. (2021); Marhain et al. (2021); Tehseen et al. (2021); Berhich et al. (2022); Turarbek et al. (2023); Bhatia et al. (2023); Sadhukhan et al. (2023); Abdalzaher et al. (2023b); Bowen et al., 2012; Zhou et al. (2020); Gitis et al. (2021); Essam et al. (2021); Xiong et al. (2021); Marhain et al. (2021); Tehseen et al. (2021); Berhich et al. (2022); Turarbek et al. (2023); Bhatia et al. (2023); Sadhukhan et al. (2023); Abdalzaher et al. (2023b)). While these technological strides have significantly deepened our insights and refined earthquake predictions, it's imperative to acknowledge that each algorithm comes with inherent limitations. This review meticulously delineates these limitations, offering a nuanced understanding of the challenges associated with predicting earthquake accuracy using diverse computational approaches.

The most recent and promising technological leap in earthquake prediction, as highlighted in this review paper, revolves around the Internet of Things (IoT). IoT-based systems leverage embedded sensors in smart devices, enabling seamless access, storage, and exchange of information either through an IoT gateway, typically a wireless connection, or by storing the acquired data in the cloud (Al-Turjman and Alturjman, 2018). An intriguing aspect of the IoT system lies in its versatility—it goes beyond facilitating information exchange solely between devices and individuals over a network. Instead, it encompasses the dynamic exchange of information directly between interconnected devices (Al-Turjman and Alturjman, 2018; Abdalzaher et al., 2023A). This evolution signifies a robust stride towards real-time monitoring and seamless data interchange among interconnected devices, charting new horizons in earthquake prediction methodologies.

Despite the significant advancements in earthquake prediction discussed above, accurately forecasting the occurrence of earthquakes remains a challenging endeavour. The failure to adequately predict events such as the devastating Turkiye-Syria doublet earthquake in 2023 (Dal Zilio and Ampuero, 2023) underscores this challenge, along with other seismic events globally. Thus, this comprehensive review aims to meticulously examine current methodologies in earthquake prediction, with the goal of identifying the most reliable approaches capable of real-time forecasting. Our methodology involves (a) thorough comparison with existing literature on earthquake prediction methods, (b) comprehensive analysis of over 480 sources, selecting 163 from reputable platforms like ScienceDirect, Springer, Frontier, IEEE, Taylor and Francis, among others, (c) detailed synthesis and review of three prominent categories of earthquake prediction methods, and (d) extensive discussion on challenges, future directions, and the pivotal role of Artificial Intelligence and IoT in shaping the landscape of earthquake prediction. Grounded in high-impact literature, this review not only elucidates the strengths and limitations of current methodologies but also offers a roadmap for enhancing and advancing earthquake prediction techniques.

1.1. Comparison with related reviews

Over the years, scientists have developed several techniques that can be used to predict earthquakes. The existing literature contains few review articles that reviewed these types of techniques. However, none of these reviews provide extensive background on earthquakes, conventional technologies, and the application of AI and IoT as the most recent technologies for predictions.

Azam et al. (2014) thoroughly examined artificial intelligence techniques used for earthquake prediction analysis. They engaged in a discourse regarding various earthquake prediction methodologies, including regression, decision trees, fuzzy logic, ANNs, SVMs, DL, Convolutional Neural Networks (CNNs), LSTM) and autoencoder. This paper presents a systematic review of earthquake prediction studies and determines that Artificial Neural Networks (ANN) and SVMs are the most prevalent and effective models for earthquake prediction. The article additionally examines the challenges that arise in forecasting earthquakes, including the acquisition, preprocessing, and post-processing of data. The authors discussed the significance of feature selection, which also emphasized several methods for feature selection, including the relief algorithm, the correlation coefficient, and mutual information. The use of swarm intelligence and its potential advantages for earthquake prediction was also deliberated by the authors. In general, the manuscript comprehensively investigates the diverse artificial intelligence methodologies employed in the prediction of earthquakes. The study's authors arrived at the conclusion that ANNs and SVMs are the most effective and commonly utilized models for earthquake prediction.

The review presented by Tehseen et al. (2020a) focuses on applying expert systems to predict earthquakes. Inclusively, the review discusses several methods, including rule-based, fuzzy, and ML variants. Despite close similarities with our review, the article does not extensively cover the IoT-based approach and open research issues. The review provided by Zhao et al. (2021) reviewed current studies on earthquake prediction. The review discusses several techniques, such as satellite-assisted monitoring and remote sensing. Furthermore, the study covers open research topics and future work. Despite this fact, the study covers several technologies, including AI and IoT, which are not extensively discussed.

The study conducted by Xie et al. (2020) covers the role of conventional technologies and ML (a subfield of AI) in earthquakes. This application ranges from seismic hazard analysis, seismic fragility assessment, structural control for earthquake mitigation, system identification, and damage detection. However, the study does not address the role of IoT, open research issues and future work. Another study focusing on the application of AI for the prediction of earthquake is provided by Al Banna et al. (2020).

Al Banna et al. (2020) provided a comprehensive review of the current state of the art in earthquake prediction using AI-based techniques. They synthesized a total of 84 articles from various academic databases that reported the use of various AI techniques such as rule-based methods, which covers all fuzzy algorithms of fuzzy logic and fuzzy neural networks, SVM, SVR, DT, PKNN, NB, HMM, KMC, HC, ANN, PNN, RBFNN, DNN, RNN and LSTM. They reported on earthquake magnitude, time, location, aftershock forecasts, and epicenter-based predictions. However, have not reported on advances state of art on the applications of IOT for earthquake predictions. The study covers several articles, which include rule-based methods, shallow ML, DL, and Clustering algorithms. Moreover, the study overview popular evaluation metrics (such as accuracy, sensitivity, specificity, Absolute Error (AE), True Positive (TP), False Positive (FP) etc.), challenges, and future work. However, the study does not cover IoT-based approaches. The review provided by Abdalzaher et al. (2022) discuses about the application of several technology in the field of seismology which include remote sensing, AI, data communication networks and other methodologies. However, despite close similarities with the current review, the review does not extensively covered earthquakes, conventional prediction approaches and open research issues. The summary of comparison with related reviews is provided in Table 1.

1.2. Scope of the review

The review is organized as follows: Section 1 of the paper captures the general introduction and background of the review. Section 2 captures the methodology for the adopted for the review procedure. Section 3 provides a background on earthquakes, conventional technologies for predicting earthquakes, reviews on existing AI-based approaches and IoT-based devices used for the prediction of earthquakes. Section 4 presents the discussion section and section 5 presents the conclusion.

2. Methodology

2.1. Research questions and objectives

Accurate and reliable earthquake prediction has long been a primary objective for seismologists and scientific experts. Therefore, the main focus of this study revolves around elucidating the roles of Artificial Intelligence (AI) and Internet of Things (IoT) in earthquake prediction, addressing the challenges posed by the dynamic nature of seismic prone environments, and exploring strategies to overcome current limitations while considering future perspectives. The motivation behind formulating these research questions stems from the scarcity of comprehensive reviews on these subjects and the pressing need underscored by events like the 2023 Turkiye-Syria doublet earthquake (M7.8) and other seismic occurrences globally. The summary of review questions is centered on: (i) Can the proposed framework effectively predict earthquakes using real-world data? (ii) What is the reliability of approaches integrating AI and IoT in earthquake prediction? (iii) What are the inherent limitations associated with these approaches? (iv) How can these limitations be effectively addressed in future research directions? As a first step, we conducted a comprehensive review of relevant literature pertaining to earthquake prediction utilizing advanced methodologies involving AI and IoT. By synthesizing these concepts, we aimed to discern novel insights into earthquake prediction, while also critically assessing the limitations inherent in these approaches. Furthermore, we endeavour to provide valuable perspectives on potential avenues for mitigating these limitations. Our methodology involved a rigorous keyword-based search to identify relevant literature for inclusion in this study.

2.2. Literature search strategy and inclusion criteria

There are several literatures that have individually studied earthquake, AI or IoT, however, there is a scarcity of literature specifically addressing the role of AI and IoT in earthquake prediction. The initial selection of articles for this review was based on a Google Scholar search using keywords such as “Earthquakes,” “Detection and prediction of earthquakes using Artificial intelligence”, " Detection and prediction of earthquakes using Machine Learning Algorithms”, “Artificial intelligence and Machine Learning in the prediction of earthquakes,” and “Application of IoT in the prediction of earthquakes”, “Detection and prediction of earthquakes using Artificial intelligence and IoT”. Our literature review aimed to identify critical issues concerning the role of AI in earthquake prediction. To achieve this, we focused on recent research and review articles published in Web of Science (Science Citation Index [SCI] and Science Citation Index Expanded [SCIE]) journals. The search for related articles utilized queries involving “Earthquakes,” “Most recent catastrophic earthquakes,” “High magnitude earthquakes,” “Artificial intelligence,” “Computational intelligence,” “Machine learning,” “Conventional methods for earthquake prediction,” “Computational prediction of earthquakes,” “IoT,” and “IoT sensors for the prediction of earthquakes,” exploring the collective role of AI and IoT in earthquake prediction.

We employed the SCI and SCIE to access articles from science journals on two main sub-topics: the overview of Al and the role of Al and IoT in predicting earthquakes. For the overview of earthquakes, we reviewed in total over 480 resources and selected 160, primarily from high-impact journals such as ScienceDirect, Springer, Frontier, IEEE, Taylor and Francis, etc. Selection criteria prioritized scientific content, peer-reviewed status, English language, and the presence of a DOI number. Among the 160 resources, 145 were research and review articles, 11 were conference papers, and 4 were books or book chapters. Additionally, 147 had DOI numbers, while 13 did not. Publication years were grouped into 8-year intervals (i.e., before 2000, 2000–2007, 2008–2015, 2016–2023). Eighty-six sources were published between 2016 and 2023, 23 between 2008 and 2015, 19 between 2000 and 2007, and 32 before 2000. For the overview of earthquakes and conventional prediction, articles from 1970 to the present were considered, while articles from 2000 to the present were used for the background of AI. For the role of Al and IoT in predicting earthquakes, articles from 2010 to 2023 were selected. All articles were in the English language. The search concluded on March 23, 2023, resulting in the retrieval of 163 articles across various sub-topics. The summary of the literature search is presented in Figs. 1 and 4 and Table 5.

3. Earthquakes

Several research projects focus on earthquake nucleation, tectonic fault ruptures, the interaction between slip modes, slow slip events, fluid-induced earthquakes, etc. (Pwavodi & Doan (2021); Uyeda and Kanamori, 1979; Lay and Kanamori, 1981; Lay et al., 1982; Davis et al., 1983; C. Scholz, 1998; Liu and Rice, 2007; Kodaira et al., 2004; Saffer and Tobin, 2011; Kitajima and Saffer, 2012; Pwavodi & Doan [2021, 2022]). Understanding fault rupture and its mechanics provide more insights into earthquake occurrence (Uyeda and Kanamori, 1979; Lay, 2016). To understand the occurrence of an earthquake, the subduction zone is highlighted since it hosts over 90% of the earthquakes in the world. In subduction zones (Fig. 2a), earthquake generation and magnitude (Fig. 2b) is closely related to the diverse nature and characteristics of the subduction zone and subduction processes (Uyeda and Kanamori, 1979). An earthquakes’ magnitude is determined by the rate at which seismic moment is released from the seismogenic zone. Wells and Coppersmith (1994); Kanamori (1977); Kanamori and Brodsky (2004) propose that the earthquake magnitude increases with the fault rupture area. (Pacheco et al., 1993) identified that the subduction thrust with earthquake magnitudes ($M < 8$) have small seismic patches

Table 1
Comparison with Related review

Reference	Earthquakes	Historical Earthquakes	Conventional Prediction	AI	IoT	Open Research Issues
Tehseen et al. (2020a)	Yes	Yes	Yes	Yes	No	No
Azam et al. (2014)	Yes	Yes	Yes	Yes	No	No
Zhao et al. (2021)	Yes	Yes	Yes	No	No	Yes
Xie et al. (2020)	Yes	Yes	Yes	Yes	No	Yes
Al Banna et al. (2020)	Yes	No	Yes	Yes	No	Yes
Sun et al. (2022)	Yes	No	No	Yes	No	Yes
This review	Yes	Yes	Yes	Yes	Yes	Yes

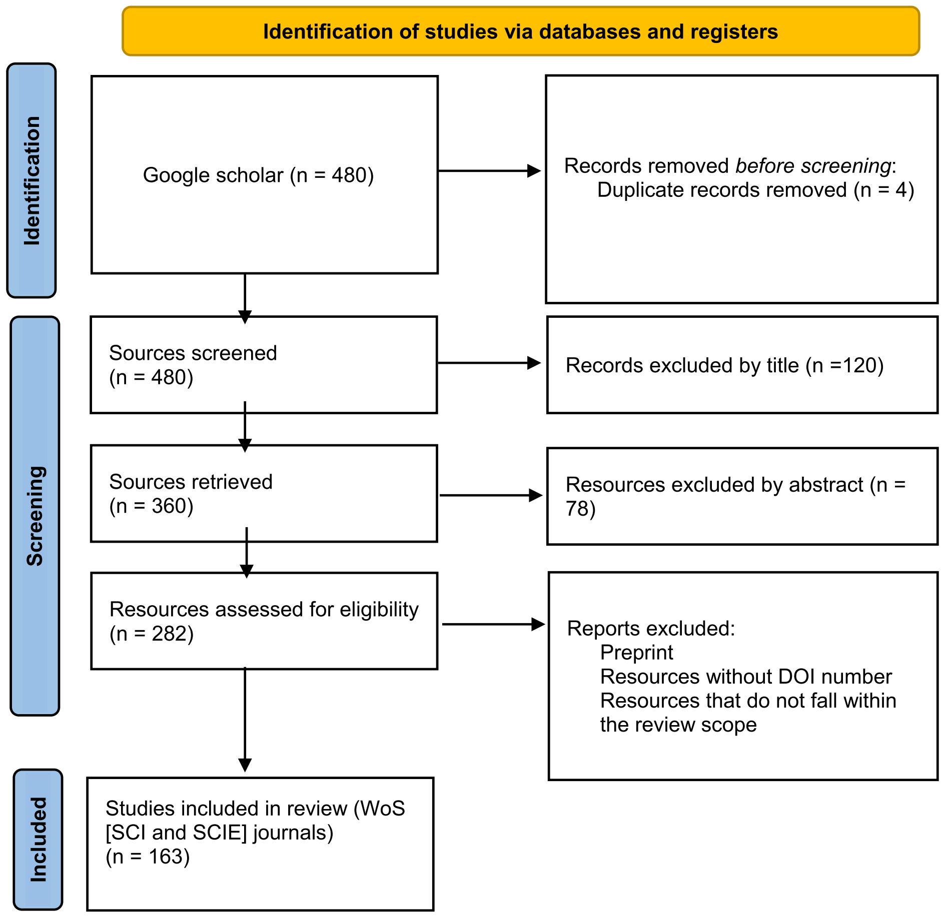

Fig. 1. Flow diagram of screening process.

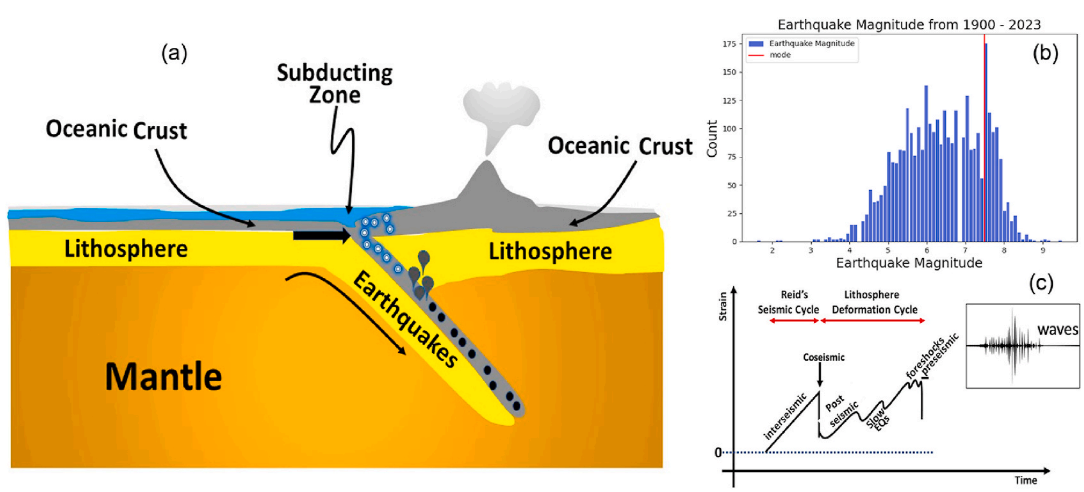

Fig. 2. (a) A simple schematic diagram of a subduction zone with earthquake occurring along the interface of the two plates. (b) A histogram plot of the different earthquake magnitude around the globe from 1900 to 2023. The red vertical line indicates the most occurring magnitudes (Mw = 7.5). (c) A simple diagram of a seismic cycle showing the interseismic interval, co-seismic and post-seismic intervals. It also shows the wave signal propagation.

supported by a small moment release rate. Large magnitude ($M > 8$) earthquakes have large seismic moment release with seismic efficiency close to unity. C. Scholz (1998) identified that seismic areas with large asperities could easily undergo seismic rupture nucleation and propagation, while areas with small asperities are limited in seismic rupture propagation.

3.1. Conventional methods for earthquake monitoring and prediction

Before we look at the attempts or precursors used to predict earthquakes based on non-scientific and scientific evidences, we highlight the different phases or cycle of the earthquake. Earthquake cycle (seismic cycle) (Fig. 2c) was developed by Harry Fielding Reid13 to explain his observations of the San Francisco earthquake of 1906. The earthquake-related deformation cycle consists of mainly four phases: the preseismic (nucleation) phase, the interseismic phase (long periods between large earthquakes during which elastic strain accumulation occurs in the broad region) (Fig. 2c), the co-seismic phase (brief period during which the accumulated strain is released during earthquakes) and the post-seismic phase (period immediately after an earthquake) (Fig. 2c) which exhibits relatively higher rates of deformation wherein the material deforms in response to the sudden coseismic release of strain (M. Li et al., 2022). List of earthquakes, earthquake magnitudes, and locations between 2000 and 2023 are presented in Table 2 (see Table 3).

There are a number of established approaches that have been used successfully in the past to accurately predict earthquakes. Seismic monitoring is a process that involves continually monitoring seismic activity in a specific location using seismic sensors called seismometers to detect, record, and analyze the seismic waves produced by earthquakes (Allen et al., 2009; Allen and Melgar, 2019). These sensors are often installed in regions that experience a high level of seismic activity, and their primary purpose is to track how that activity evolves over time (Allen et al., 2009; Allen and Melgar, 2019). The data collected from seismic monitoring is analyzed using a variety of techniques, including waveform analysis (Stein and Wysession, 2003; Bondàr et al., 2015), spectral analysis (Delsemme and Smith, 1979; Ross et al., 2016; Boatwright and Seekins, 2011) and pattern recognition (Curilem et al., 2014; Mosher and Audet, 2020; Zhizhin et al., 2006).

Table 2
List of earthquakes, earthquake magnitudes, and locations between 2000 and 2023.

Year	Tsunami	Magnitude (Mw)	Location
2023		7.8	Turkey (South Eastern Anatolia)
2019		8.0	Peru (La Libertad), Cajamarca (Equador)
2018	Tsunami	7.9, 7.8 and 8.2	Alaska (Kodiak Island), Fiji Islands
2017	Tsunami	7.7, 7.9, 8.2	Russia (Bering Island), Papua New Guinea (Bougainville Island), Mexico (Oaxaca), Chiapas, Tabasco (Guatemala)
2016	Tsunami	7.6, 7.8, 7.8, 7.8	Chile, Indonesia (Sumatra), New Zealand (Amberley), Solomon Islands
2015		7.6, 7.8, 7.8, 8.3	Peru-Brazil, Nepal: Kathmandu, India, Chile
2014	Tsunami	7.6, 7.7, 7.9, 8.2	Solomon Islands, Chile (Iquique), Alaska (Aleutian Islands), Alto Hospicio
2013	Tsunami	7.7, 7.6, 7.9, 8.3	Scotia sea (south Orkney Islands), Pakistan (Awaran Kech), Solomon Islands (Santa Cruz Island), Russia (Severo Kurilskiye)
2012	Tsunami	7.6, 7.6, 7.7, 8.2	Phillipines (Cagayan De Oro Tacloban), Costa Rica (Nicoya), Canada (queen charlotte Islands), Indonesia (sumatra)
2011	Tsunami	7.6, 7.6, 7.9, 9.1	New Zealand (Kermadec Islands), Japan (Off East Coast Honshu), Japan (Honshu)
2010	Tsunami		7.8, 8.8 Indonesia (Sumatra), Chile (Maule), Talcahuano
2009	Tsunami	7.6, 7.6, 7.6, 7.8 8.1	Vanuatu Islands, Papua New Guinea (Near North Coast), Tonga Islands, New zealand (Off West), Coast of South Island, Samoa Island
2007	Tsunami	7.7, 7.8, 8.0, 8.4 8.1	Chile (Tocopilla), Maria Elena, Kermadec Islands, Peru (Ica, Pisco, Lima), Solomon Islands, Indonesia (Sumatra)
2005		7.6,7.7,7.7	Pakistan (Muzaffarabad, Baramula), Papua New Guinea (New Ireland), Chile (Tarapaca)
2004	Tsunami	8.1, 9.1	Australia (Macquarie Island), Indonesia (Sumatra)
2003	Tsunami	7.8, 8.3	Alaska (Aleutian Islands, Rat Islands), Japan (Kokkaido)
2002	Tsunami	7.6	Indonesia: New Guinea, Manokwari, Oransbari, Ransiki, Papua New Guinea, Wewak.

Table 3
Table showing some sensors used for IoT earthquake detection.

IoT-Sensors	Features	Attributes observed for earthquake
Seismic sensors	Ground motion	Motion of the ground due to earthquake
Seismometers, Noise sensors	Seismic noise	Ground shaking noise
Water level sensors	Groundwater levels	The water saturation level of the ground
Location sensors	Latitude of the earth	North South position of a point on the earth surface
Epicentre sensors	Epicentre	The point on the earth surface that is directly above the focus of an earthquake

Scientists are able to recognize patterns and shifts in seismic activity that may be a precursor to the occurrence of an imminent earthquake by conducting an analysis of seismic data. Monitoring seismic activity is an essential part of the study of earthquake prediction, and its results are incorporated into early warning systems (Allen and Melgar, 2019; Mosher and Audet, 2020). Over the years there has been several types of seismometers used for earthquake monitoring both on land and ocean such as; short-period seismometers, strongmotion seismometers, broadband seismometers, MEMS seismometers, accelerometers, OBS, DAS systems, array seismometers and superconducting gravimeters (Yoshimitsu et al., 2004; Allen and Kanamori, 2003; Waldhauser and Ellsworth, 2000; Gonzalez-Herraez et al., 2021; Shinohara et al., 2022; Fern'andez-Ruiz et al., 2020; Shan et al., 2017; Yoshimitsu et al., 2004). These systems can be of great assistance to both individuals and communities in the event of an earthquake by providing vital information.

Various remote sensing methods have been used to spot changes in ground deformation and surface anomalies that can predict earthquakes as well as attenuation of the seismic ground motion amplitude which is crucial for determining the chances of heavy ground shaking (Moustafa et al., 2023). These methods include satellite data, GPS, and InSAR (Dong and Shan, 2013; Hardeep Panchal et al., 2022; Didier et al., 1994; Thompson and Wright, 2002). High-precision GPS receivers can estimate the position and movement of ground points; tracking the movement of GPS base stations over time can reveal subtle tectonic shifts (Su et al., 2016; Tronin, 2010; Thompson and Wright, 2002). Earthquakes could occur as a result of tectonic plate shifts. Chen et al. (1999) analyzed GPS data to better understand the dynamics of the M7.7 Chi-Chi earthquake that struck Taiwan in 1999, providing a prime example of how GPS can be used for earthquake prediction. The researchers used GPS data to determine that the earthquake caused significant crustal displacement. Su et al. (2016) conducted a similar analysis using GPS data to identify abnormal crustal deformation in the years leading up to the 2014 M6.1 Ludian earthquake in China. Moustafa et al. (2023) integrates several features which include structural, geophysical, remote sensing and seismic activity in order to explore the link between tectonic structures and seismotectonic activity in Egypt. Moreover, the authors applied Computer-assisted software for the automated lineament extraction using a database that contains 8000 lineaments.

In addition to the GPS, other satellite-based technologies like InSAR which uses the radar signals have also been utilized for the purpose of predicting earthquakes (Wang and Abriak, 2015; Berardino et al., 2002; Bürgmann et al., 2000). InSAR provides millimeter accuracy of surface deformation and is important for detecting preseismic deformation and postseismic displacement (Wang and Abriak, 2015; Bürgmann et al., 2000; Massonnet and Feigl, 1998).

Other methods of predicting earthquakes, such as monitoring of radon gases, are still very debatable. Prior to the occurrence of an earthquake, several microfractures form within the ground due to tectonic stresses build up (Cicerone et al., 2009; Riggio et al., 2015; Igarashi and Wakita, 1990; Allegri et al., 1983). These fractures serve as an escape route for a radioactive gas called radon gas. This gas is used as an indicator of seismic activity. Researchers are using radon gas monitoring to detect changes in radon gas levels that may be indicative of imminent earthquakes (Cicerone et al., 2009; Hauksson and Goddard, 1981; Igarashi and Wakita, 1990; Allegri et al., 1983; Woith, 2015; Garavaglia et al., 1998; Alessio et al., 1980; Papastefanou et al., 1989). The monitoring of radon gas has been suggested as a possible method for earthquake prediction; nevertheless, the scientific community is currently debating the accuracy of this method in this regard (Woith, 2015; Riggio et al., 2015). In general, while the monitoring of radon gas may be one tools for earthquake prediction, it is not generally considered to be a reliable or accurate strategy on its own. Although researchers are still investigating the link between radon gas and earthquakes, other techniques, such as seismic monitoring and GPS, are now considered more reliable for predicting earthquakes (Woith, 2015; Cicerone et al., 2009; Hauksson and Goddard, 1981; Igarashi and Wakita, 1990; Allegri et al., 1983; Riggio et al., 2015).

3.2. *Artificial intelligence and its role in earthquake prediction*

3.2.1. *Definition, history and types of AI*

AI is a sub-field under computer science that uses computers to mimic human cognitive behaviours such as memory retention, learning, decision-making, problem solving, etc (Kok et al., 2009). The concept of AI was coined by John McCarthy et al. (2006) and ever since the domain have encountered significant improvement and applicability in different field (Fig. 3) (Russell and Norvig, 2010). The concepts of AI and Machine Learning (ML) are used interchangeably; however, ML is an AI subset where algorithms learn from data, improving performance autonomously, recognizing patterns, and making predictions (McCarthy et al., 2006; Hastie et al., 2009). ML algorithms are grounded in mathematical principles such as linear algebra, calculus, and probability theory, transform input information into predictive models (Hastie et al., 2009, Russell and Norvig, 2010). Types of ML algorithm include supervised learning (SML), unsupervised learning (UML) and reinforcement learning (reward-based learning through trial and error) (Hastie et al., 2009; Russell and Norvig, 2010; Alzubi et al., 2018; Morales and Escalante, 2022). (a) Supervised learning algorithms use labeled data to minimize the difference between predicted and actual outputs. Most of the applications of SML models revolve around regression or classification, hence solving linear, non-linear, multiple, and logistic regression problems (Russell and Norvig, 2010). (b) Unsupervised learning algorithms, like k-means clustering and principal component analysis, uncover hidden patterns within unlabeled data. Some of the advantages of UML include the ability to use real-time data, ease of use and less expensive. However, UML can disadvantageously produce an unpredictable outcome and difficulty of measuring the effectiveness of the models (Jordan and Mitchell, 2015; Morales and Escalante, 2022).

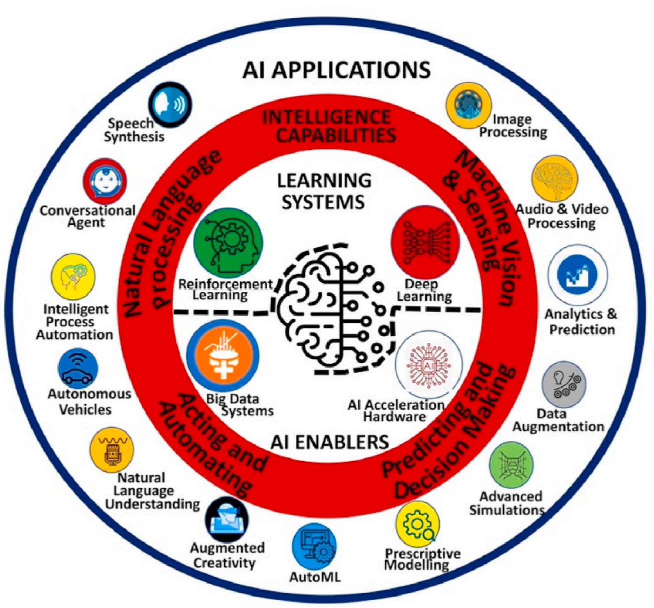

Fig. 3. Applications of artificial intelligence.

3.2.2. *The role of AI in the prediction of earthquakes*

Recently, several works have leveraged on the complex predictive capacity of ML algorithms to analyze complex patterns in historical seismic activity, meteorological data, acceleration, velocity data etc to predict earthquake (Fig. 4) (Mirrashid, 2014; Lim et al., 2020; Tehseen et al., 2020b; Yousefzadeh et al., 2021; Aslam et al., 2021; Aslam et al., 2021b; Berhich et al., 2022; Bhatia et al., 2023). AI-based works have lately adopted Neural Networks (NN), ML, and DL algorithms and other approaches (Mirrashid, 2014; Tehseen et al., 2020b, 2020a; Yousefzadeh et al., 2021; Aslam et al., 2021). ML algorithms have predicted short-term earthquakes, while statistical and mathematical approaches have predicted medium to long-term earthquakes (Mirrashid, 2014; Lim et al., 2020; Tehseen et al., 2020b; Yousefzadeh et al., 2021; Aslam et al., 2021). ML and DL earthquake prediction studies used classification or regression (Mirrashid, 2014; Lim et al., 2020; Tehseen et al., 2020b; Yousefzadeh et al., 2021; Aslam et al., 2021; Aslam et al., 2021; Berhich et al., 2022; Bhatia et al., 2023) (Fig. 4).

Zhou et al. (2020) introduced an earthquake prediction model based on artificial immunity and the danger theory. Grounded in the Gutenberg-Richter (GR) inverse power-law, the danger theory was applied due to the absence of a clear empirical relationship between seismicity features, earthquake magnitude, and location within a specific time window. The authors proposed a second-order numerical differentiation approach to extract signals using the Dendritic Cell Algorithm (DCA). Subsequently, they utilized the new version of ndDCA for earthquake prediction. The earthquake indicator system was compiled from various levels of features during seismic silence and activity periods. Furthermore, these earthquake indicators were transformed into input signals in ndDCA through numerical differentiation. The model demonstrated the capability to predict earthquakes with a magnitude of 4.5. The researchers conducted a comparative analysis with other machine learning algorithms, including KNN, Haskell-based deterministic DCA (hDCA), Negative Selection Algorithm (NSA), Back Propagation Neural Network (BPNN), and SVM. The findings indicated that the earthquake prediction model based on ndDCA (EQP-ndDCA) surpassed all other models in performance. However, the study acknowledged the ongoing need for methodological enhancements to better capture the high variability and uncertainty associated with earthquake data monitoring.

Xiong et al. (2021) introduced a ground breaking framework for earthquake forecasting. The authors presented the novel Inverse Boosting Pruning Trees (IBPT) model, which leverages satellite data encompassing ten parameters, including infrared sensing, hyperspectral imaging, and gas sensing signals. The dataset was collected from global earthquakes occurring between 2006 and 2013. The IBPT model, inspired by Convolutional Neural Network principles, features four layers and utilizes input data derived from a comprehensive set of seismic events. This dataset includes 1234 earthquakes with magnitudes between 6 and 7 and 137 earthquakes with magnitudes exceeding 7, covering diverse regions globally. To assess its efficacy, the IBPT model's performance was compared against eight different state-of-the-art machine learning methods. Despite achieving a R score >0.6, the IBPT model is constrained by significant computational complexity due to the extensive iteration requirements during the pruning process.

Essam et al. (2021) conducted research to investigate the accuracy of various AI techniques in predicting earthquakes in Malaysia. The AI methods used for the prediction of earthquakes in their works are ANN,

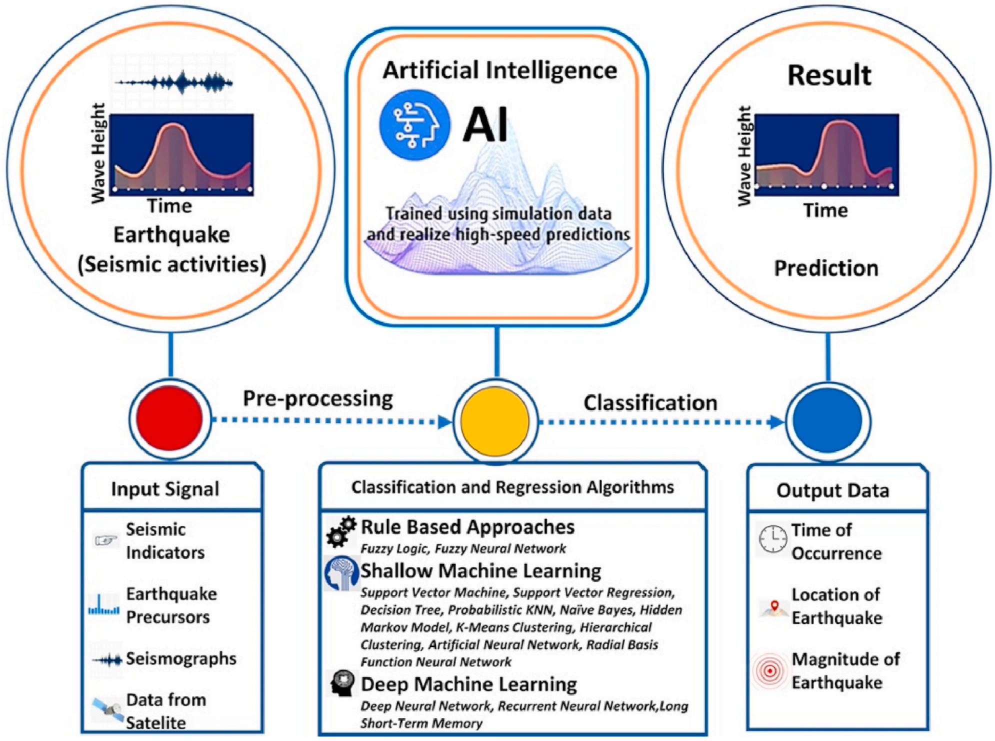

Fig. 4. The Role of AI in the processing of data obtained from seismic activities used in Earthquake Prediction.

SVM, KNN, NB, Quadratic Discriminant Analysis (QDA), RF, and Logistic Regression (LR). The study relied on data from the Malaysian Seismic Network. The authors assessed the performance of the model using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Square Error (MSE), and discovered that SVM, KNN, and RF outperformed ANN, NB, and LR. They discovered that the SVM model performed the best using the RMSE, MAE, and MSE, respectively. They also suggested that the SVM model be used for additional research and development in earthquake prediction in Malaysia.

Marhain et al. (2021) delved into the application of Artificial Intelligence (AI) for earthquake prediction in Terengganu, Malaysia. The study involved the analysis of meteorological data from multiple stations in Terengganu using Machine Learning (ML) methods. Four distinct models were investigated in the research, namely Support Vector Machine (SVM), Boosted Decision Tree Regression (BDTR), Random Forest Regression (RFR), and Multivariate Adaptive Regression Spline (MAR Spline). The authors rigorously evaluated these models using various metrics, including correlation coefficient, root mean square error, and mean absolute error. Through comprehensive comparisons, the study revealed that BDTR outperformed the other model algorithms in predicting earthquake occurrence concerning time, acceleration, and depth. The overall assessment, for instance, indicated that the results in terms of R2 score fell within the range of 0.3–0.7. However, a notable limitation of the study was the challenge posed by the unavailability or sparsity of data in different meteorological stations. To address this issue during model training and prediction, some stations' data were either dropped or augmented, introducing a potential source of bias in the findings.

Gitis et al. (2021) assessed the effectiveness of utilizing GPS data, specifically time series of surface displacements, for systematic earthquake prediction, particularly for events with magnitudes exceeding 6.0 in Japan (2016–2020) and over 5.5 in California (2013–2020). Employing machine learning, specifically the minimum area of alarm method, the research compares prediction outcomes using random forecasts, seismic density-based predictions, and spatio-temporal fields derived from GPS and seismological data individually and in combination. The evaluation criterion is the probability of successfully predicting earthquakes within a constrained alarm zone. Results consistently demonstrate the efficacy of GPS data, either alone or integrated with seismic information, for enhancing systematic earthquake prediction, showcasing the potential of space geodesy in bolstering the accuracy of seismic forecasting efforts.

Abdalzaher et al. (2021a) addresses the challenge of discriminating between seismic events and quarry blasts in the northeastern part of Egypt, where the seismicity catalog is contaminated by quarry blasts. A robust machine learning (ML) model is proposed to decontaminate the seismicity database, specifically focusing on events with magnitudes <3, prone to high uncertainty in classification. Leveraging 870 events observed by the "GLL" seismic station, the model evaluates various linear and nonlinear ML models, ultimately selecting the extreme gradient boosting (XGB) model. Through a meticulous optimization process, the scheme achieves 100% discrimination accuracy between earthquakes and quarry blasts. The significance of this model lies in its ability to contribute to the proper delineation of earthquake clusters, facilitating more accurate seismic hazard assessments in the region and aiding in sustainable urban development planning.

Tehseen et al. (2021) published a novel study on earthquake prediction frameworks using Federated Learning (FL). The authors stated that the proposed FL framework performed better than the previously developed ML-based earthquake prediction models using the parameters of efficiency, reliability, and precision. They generated multiple ML-based local data models using three different local datasets for their analysis. The authors also stated that they compiled a global data model from the local data models on the central FL server using the FedQuake algorithm. They also used a Meta classifier which was trained using the global data model at the FL server. This was done to provide more accurate earthquake predictions. They also stated that their proposed tested framework was used to analyze multidimensional seismic data from the western Himalayas. The authors also applied their model on regional seismic data from the previous thirty-five years, yielding a higher prediction accuracy. This could be used in the development of earthquake prediction models.

Considering the idea that Seismic site classification is the most accepted approach for the design of seismic resistant infrastructure. Thus, the used of data-driven and unsupervised-based ML approach for preliminary seismic site-specific classification maps is proposed by Moustafa et al. (2021a). In order to characterize site of interest, a clustering ML technique which relies on Adaptive Affinity Propagation (AAP) technique and the Horizontal To Vertical Spectral Ratio (HVSR) method for analysing ambient noise data. Measurements of the ambient vibrations were conducted in order to cover the entire site by about 307 stations. Moreover, the recording at each station lasted for 20 min and 128HZ sample rate. Values obtained which include frequency and amplification are utilized for site classification by passing information between data points. The outcome of the approach demonstrated the efficiency of the microtremor spectral ratio and it prospects as a tool for determining site effects. In another study, Moustafa et al. (2021b) implemented different regression models for the prediction of Peak Particle Velocity (PPV) by using a dataset that contains 1438 blast incidents. In order to evaluate the output performance of the predictive model, RMSE and the coefficient of determination (R^2) are used. The result achieved indicated proof of higher performance in the developed Decision Trees model with the highest R^2 and lowest RMSE values.

Bilal et al. (2022) introduced an advanced Early Warning System (EWS) for earthquake prediction based on the BNGCNNATT model. The model combines Batch Normalized Graph Convolutional Neural Network (BNGCNN) with an attention mechanism. The Convolutional Neural Network (CNN) component of the model utilizes a convolutional layer to extract crucial information from seismic raw waveform data collected from multiple stations. The information extracted by the convolutional layer is then utilized by the attention layer to enhance the feature map, emphasizing the most valuable components of the signal. The Graph Neural Network (GNN) analyzes spatial data and meta-data related to the base stations. The inclusion of a batch normalization layer before the activation layer contributes to improved learning and shorter training times. The method was applied to datasets from Alaska and Japan, both characterized by dense seismic activity, to predict earthquake magnitudes. The Root Mean Square Error (RMSE) values obtained from both datasets demonstrated that the proposed BNGCNNATT model significantly outperformed baseline models for magnitude estimation.

Berhich et al. (2022) introduces a location-dependent earthquake prediction method employing recurrent neural network algorithms. Employing K-Means clustering based on geographical parameters, each region is divided into subsets, focusing on specific magnitude ranges. The models, including Long Short Memory (LSTM), Gated Recurrent Network (GRU), and their hybrid (LSTM-GRU), exhibit robust performance across three distinct regions: Morocco, Japan, and Turkey. The authors reported that clustering the datasets allowed their model to analyze each region independently, and the splitting methods aided their model in training it to know the trends of each cluster separately with their accurate performance. Evaluation metrics, including mean absolute error, mean squared error, and root-mean-square error, demonstrate the models' effectiveness, particularly in predicting significant earthquakes. This approach shows promise, outperforming existing literature in earthquake prediction, especially for larger seismic events.

Considering the fact that effective handling and planning approaches for development of urban regions require vast range of thematic information as well as acquisition of uncontaminated catalogue of seismic data is crucial for the evaluation of earthquake clusters spatial allocations. In light of this, Abdalzaher et al. (2022b) focus on North-eastern part of Egypt in which the seismicity catalogue is contaminated by Quarry Blasts (QBs) operated throughout the mapped area. The study proposed an efficient ML model (both linear and non-linear) which are applied for the decontaminating the seismicity database so that the clusters can be precisely delineated. The best model is selected based on 2 features which led to the optimal discrimination between EQs and QBs. Evaluation of the ML models prove that the framework achieved 100% accuracy in discrimination between EQs and QBs.

Turarbek et al. (2023) introduces a novel end-to-end strategy to enhance earthquake detection accuracy by refining each step of the detection pipeline. It proposes a Conv2D convolutional neural network (CNN) architecture for processing seismic waveforms, outperforming various machine-learning approaches and state-of-the-art methods. The Conv2D model, evaluated on 97 years of seismic data from Kazakhstan (1906–2022), achieved superior accuracy, precision, recall, and f-score scores at 63%, 82.4%, 62.7%, and 83%, respectively. The results affirm the efficacy of the proposed Conv2D model in predicting real-world earthquakes within seismic zones, showcasing its potential in seismic event forecasting. The results, while promising, highlight the model's instability due to insufficient training data. The hypothesis posits that earthquake events exhibit cyclical patterns, and relying solely on magnitude and depth predictors for retro data may predict future destructive earthquakes.

Bhatia et al. (2023) present a study of "artificial intelligence-based real-time earthquake prediction." The authors proposed a work using an IoT-Edge-centered smart earthquake monitoring and prediction framework that uses cloud and edge computing methods. This study proposes a collaborative IoT–Edge-based earthquake monitoring and prediction framework, integrating cloud and edge computing. IoT technology captures real-time sensor data, processed at the edge layer using a Bayesian belief model for feature classification. The cloud layer employs the Adaptive Neuro-Fuzzy Inference System (ANFIS) for earthquake magnitude forecasting. Experimental results showcase the framework's enhanced classification performance (Precision 92.52%, Sensitivity 91.72%, Specificity 91.01%), reduced computational delay (23.06s), and improved reliability (95.26%) and stability (92.16%). This model demonstrates the potential for intelligent earthquake prediction with heightened accuracy and efficiency.

Sadhukhan et al. (2023), used DL techniques for the prediction of earthquake magnitude using eight mathematically calculated seismic indicators that have been mathematically calculated derived from earthquake databases in Japan, Indonesia, and the HinduKush Karakoram Himalayan (HKKH) region. The authors used three DL methods: LSTM, Bi-directional Long Short-Term Memory (Bi-LSTM), and self-attention-based transformer (SABT). These DL methods were used to compare the relationships between seismic indicators and earthquake events. The authors evaluated the models using MAE, MSE, Log-Cosh Loss (LCL) and Mean Squared Logarithmic Error (MSLE). Their results were able to predict accurately the magnitudes of earthquakes. They also tested their model on unfamiliar datasets obtained from Japan. The model gave an excellent result for LSTM for Japan, Bi-LSTM for Indonesia, and the transformer model for the HKKH regions. The authors concluded that their developed model could predict earthquakes of magnitudes ranging from M3.5 to M6.0.

Abdalzaher et al. (2023b) introduces an on-site 2-s Machine Learning Earthquake Intensity Determination (2 S-ML-EIOS) model for quick identification of earthquake intensity after 2 s from the P-wave onset, crucial for early warning systems. Leveraging an Internet of Things (IoT) network, the model employs various linear and nonlinear machine learning models, with a focus on the extreme gradient boosting (XGB) model, to achieve reliable intensity estimation. Trained on a dataset from 386 stations in the Italian national seismic network, the 2 S-ML-EIOS model demonstrates an impressive 98.59% accuracy rate in predicting earthquake intensity. The proposed model, when integrated into a centralized IoT system, can promptly send alarms and instruct affected administrations for timely actions, showcasing its efficacy for Earthquake Early Warning Systems (EEWS). The enhanced performance of the XGB model underscores the methodology's effectiveness in earthquake intensity determination.

3.3. Internet of Things (IoT) and its role in earthquake prediction

3.3.1. Definition, history, components and types of IoT

The term "Internet of Things" (IoT) originated in 1999 within the Radio Frequency Identification (RFID) development community. Coined to represent the integration of technologies like AI, Information and Communication Technology (ICT), and data analysis (Wortmann and Flüchter, 2015), IoT serves as a platform connecting myriad physical objects, including devices and sensors. These entities gather and exchange data via the Internet (Wortmann and Flüchter, 2015; Al-Turjman and Alturjman, 2018). While proposed over two decades ago, widespread attention from researchers and investors materialized in the past decade (Wortmann and Flüchter, 2015; Al-Turjman and Alturjman, 2018). IoT centers on sensor connectivity in devices like mobile phones, monitors, and computers. Its recent surge has yielded diverse applications across environmental sciences, architecture, smart homes, healthcare, and industries (Al-Turjman and Alturjman, 2018; Aman et al., 2020).

IoT-based devices are designed with unique identifier which enable them to exchange information with other devices without the need of human intervention (Rose et al., 2015; Mora et al., 2018). IoT system revolves around connectivity, communicating and exchange of data according to designed protocols for the aim of achieving real-time monitoring, smart reorganization, tracing, positioning, safety, process control (Mora et al., 2018; Khodadadi et al., 2016). IoT system is made up 3 basic components which include (a) Devices that have sensors that detect physical changes, record them, and store or transfer data to other devices or servers (Wortmann and Flüchter, 2015). (b) Software that connects hardware board and internet in these systems. Thus, the software in IoT devices is used mostly for configuration and management (Shah and Mahmood, 2020). (c) Networking/Internet refers to systems or frameworks that network devices. Thus, the internet connects hardware devices to people, stores data in memory or the cloud, and drives and transmits data. Thus, the internet underpins IoT systems (Gowda et al., 2020). IoT have nodes that help with local data processing, which decreases latency and improves real-time processing capabilities: Some of the types are highlighted here.

3.3.1.1. Types of IoT nodes. IoT nodes types are characterized by distinct technologies, operational lifetimes, power consumption, and their nodes serve as integral components for earthquake monitoring systems. The suitability of different IoT nodes for earthquake monitoring is contingent upon factors such as their power efficiency, communication capabilities, and sensor technologies (Lee et al., 2019; Le Breton et al., 2022; Song et al., 2023). Some IoT nodes types.

- Gateway nodes serve as vital components in network infrastructures, and positioned at the interface between different communication protocols (Fig. 5), these nodes enable seamless connectivity, translation, and coordination among IoT devices with varying standards (Elkhodr et al., 2016; Vila et al., 2023). Gateway nodes help in aggregating and forwarding data to centralized systems or the cloud, contributing to efficient data management (Elkhodr et al., 2016). Equipped with protocols such as Message Queuing Telemetry Transport (MQTT) or Constrained Application Protocol (CoAP), they ensure interoperability and enable devices with different communication protocols to interact harmoniously (Seoane et al., 2021).
- Edge computing nodes are crucial elements in distributed computing architectures, strategically located in close proximity to data sources and end-users (Hamilton, 2018). Edge computing nodes, which possess processing capability, storage, and communication interfaces, effectively manage tasks that need close proximity to the sites where data is generated (Fig. 5). This decentralized strategy enhances response times, reduces data transmission, and optimises bandwidth utilisation (Hamilton, 2018; Pourabdollahian et al., 2022). Edge computing nodes are crucial in meeting the increasing need for fast and efficient computation in modern digital ecosystems.
- Wireless sensor nodes, integrating low-power microcontrollers and various sensors, form the backbone of IoT networks. In Fig. 6a, the typical structure of a Wireless Sensor (WS) node is depicted, comprising five fixed modules and one configurable module. The fixed components encompass a stationary power source, which may function as a rechargeable battery (Wang et al., 2012; Jamshed et al., 2022). A controller oversees the WS node's operation and maintenance by processing data and executing essential tasks. Additionally, a memory module is commonly integrated to cater to application-specific needs and handle programming tasks, including algorithm implementation (Jamshed et al., 2022; Elkhodr et al., 2016). A transceiver facilitates communication with other WS nodes, transmitting sensory data (Jamshed et al., 2022; Elkhodr et al., 2016). Furthermore, an analogue-to-digital converter is employed to convert analog signals. This modular structure ensures the effective functioning and adaptability of the WS node in various applications. Advantageously the technology of WS generally employs energy-efficient sensors such as those for temperature, humidity, and light (Moiş et al., 2018).

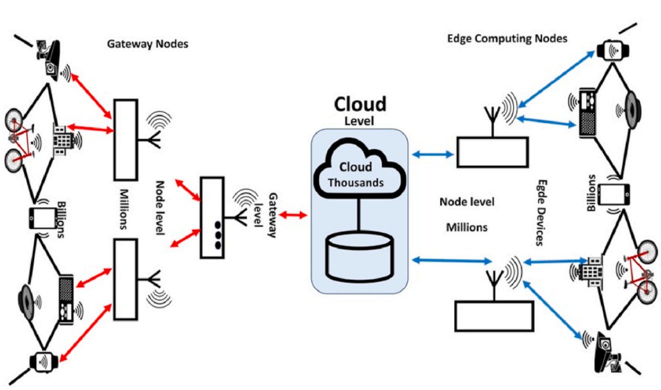

Fig. 5. Schematic architectural design of the Gateway nodes (left part of the Figure) and Edge computing node (right part of the Figure).

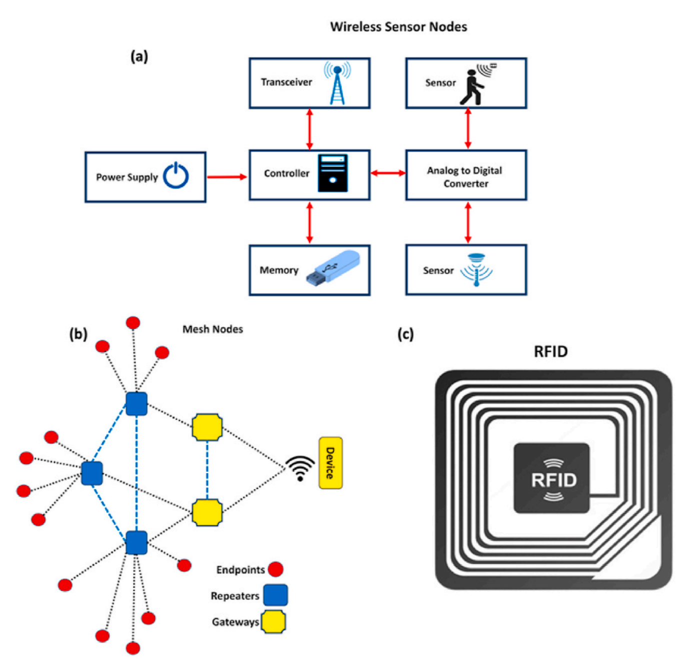

Fig. 6. Schematic architectural design of the (a) Wireless sensor nodes (b) Mesh Network (c) RFID.

- Mesh nodes, designed for efficient communication within a mesh network and operate by forming interconnected networks, allowing seamless data transmission and collaboration among nodes (Fig. 6b). The technologies incorporated in mesh nodes, such as wireless communication protocols and robust sensor capabilities, empower earthquake monitoring systems (Fischer et al., 2009; Boccadoro et al., 2019; Lee et al., 2019). The architecture is made of three components: Endpoints are used for sending or receiving data. Repeaters extend network range, relaying data between endpoints. Gateways connect the mesh network to external networks, like the internet, facilitating data exchange. The mesh nodes often utilize low-power and long-range communication technologies, ensuring extended operational lifetimes and minimized power consumption. Together, they create a robust, scalable architecture for seamless communication in various applications, from smart homes to industrial settings. Additionally, their adaptability to challenging terrains and dynamic environmental conditions and real-time data acquisition makes them well-suited for earthquake-prone areas and earthquake monitoring.
- Ultrahigh-frequency (UHF)-band radiofrequency identification (RFID) emerges as a solution (Fig. 6c), offering thin, small form factors, cost-effectiveness, and batteryless wireless capabilities (Lee et al., 2019; Le Breton et al., 2022; Hillier et al., 2019; Song et al., 2023). A RFID system comprises an RFID reader, tag antenna, and integrated circuit (IC) chip (Lee et al., 2019; Le Breton et al., 2022; Hillier et al., 2019; Song et al., 2023) with the reader emitting radio waves to RFID tags, receiving unique electronic product codes (EPCs) in return (Lee et al., 2019; Le Breton et al., 2022; Hillier et al., 2019; Song et al., 2023). Overall, the RFID sensor leverage both passive and active technologies, enable identification and tracking (Lee et al., 2019). Its functionality and architecture make RFID suitable for measuring various environmental parameters, including vibrations, movements, and physical shocks (Song et al., 2023).

3.3.2. The role of IoT in the prediction of earthquakes

The IoT system can be summarized (Fig. 7), to have three levels (i) the local platforms that contain the smart objects or sensors that communicate with each other and interact with the environment; (ii) a transport platform that allows the sensors to communicate with the higher-level platforms or infrastructures; and (iii) a storage, data analyses, and processing platform. It is usually integrated into the cloud, and combined with systems and other interfaces to allow users to access and visualize the data that has been analyzed, and further predictions can be made accurately using real-time data (Bhatia et al., 2023; Saini et al., 2022; Esposito et al., 2022; Mia et al., 2021; Abdalzaher et al., 2023c). The authors have employed IoT in the detection of seismic signals, as proposed by Zambrano et al. (2017) & Atzori et al. (2012), for detecting and predicting earthquakes, sending alerts to nearby smart devices connected to the sensors responsible for detecting earthquakes (Fig. 7). There are wearable devices that are used in IoT, according to Pirmagomedov et al. (2018), which may give rise to noisy data communication in their results. Sarwar et al. (2019) developed a smart fire detection system using IoT to provide early warning alerts when a fire outbreak occurs. P. Li et al. (2017) extracted features from big data using a deep convolution computation model from IoT. Ray et al. (2017) reported on the significance of IoT in managing disaster, resources, policies formulation, and faster communication (see Fig. 8).

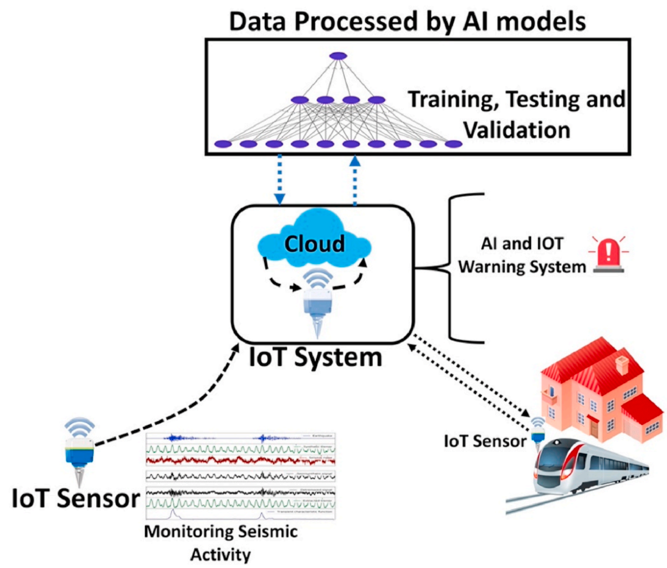

Fig. 8. The structure of AI and IoT integrated together and used in Earthquake Prediction.

Lu et al. (2020) published a work on federated learning techniques protected by privacy that can address data sharing by communicating a data model developed rather than actual data through blockchain technology. Pirmagomedov et al. (2018) published a review work on IoT Based Earthquake Prediction Technology. The review article enabled them to formulate new tasks which can serve as a solution that can be used to improve the previous methodologies that mentioned the use of animals for biosensing. Their proposed system was used to collect data

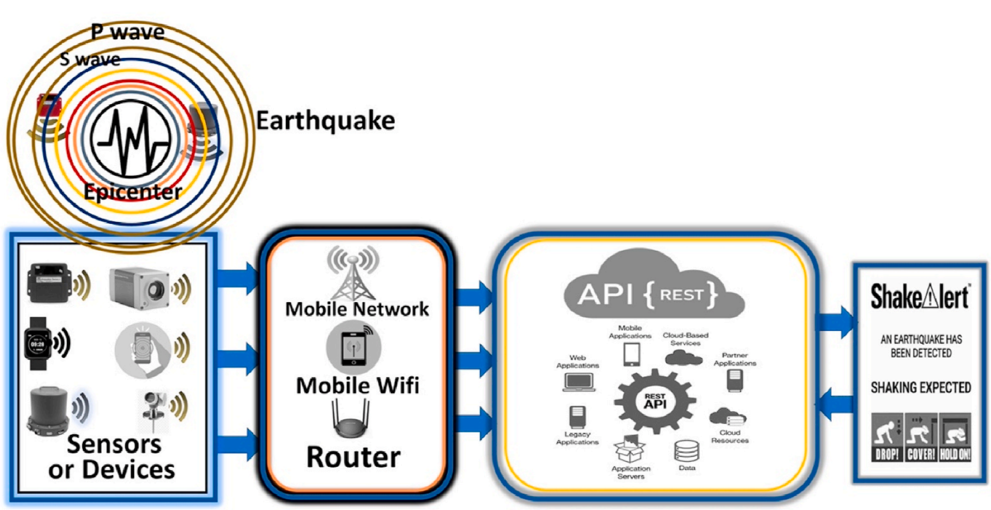

Fig. 7. The general structure of IoT platform and its role in Earthquake Prediction.

from the behavior of animals using inertial sensors and computer vision. After this, they processed and analyzed the data using the central server. They concluded by saying that if there would be a change in the system, as in any earthquake occurring, then the non-standard behavior of the animals should be observed and used as indicators to predict the earthquakes.

Esposito et al. (2022) provided an in-depth review on the literature on 'recent advances in IoT solutions for EWS.' Their work reviewed the literature on IoT solutions used as Early Warning systems for natural disasters such as floods, earthquakes, tsunamis, and landslides. The authors could describe the IoT architectures and structure systems used for predictions of natural disasters and also give the limitations and requirements of such early warning systems. They also determined which of the solutions are mostly used for natural disasters. The authors also described the shortcomings and main gaps in the reviewed literature by providing suggestions based on the solutions reviewed in the literature, emphasizing the importance of combining the IoT architectures developed with Fog/Edge layers.

Saini et al. (2022) proposed work on "An integrated framework for smart earthquake prediction; IoT, fog, and Cloud Computing." The authors reported on collaborating on an IoT-based earthquake smart monitoring device and a framework for predicting earthquakes, such as fog and cloud computing. The proposed model was used to obtain data from the IoT sensors and then transfer the data to the fog layer, which is responsible for preprocessing the data, feature extraction, selection, and classifying the data using the random forest technique. The authors then used the ANFIS in the cloud layer to predict the magnitude of the earthquake. Their result demonstrated the ability of the model to monitor and predict earthquakes. Finally, adding the fog layer has reduced delay and increased accuracy, making the analysis more real-time.

3.4. The role of both AI and IoT in predicting earthquake

This section investigates the importance of integrating IoT and AI in monitoring earthquake prediction (Table 4). The combination of IoT and AI in the prediction of earthquakes has offered advantages in managing pre- and post-disaster management when predicting earthquakes (Fig. 5). Abdalzaher et al. (2021b) proposed a DL model that combines an autoencoder and a CNN to identify and monitor the magnitude and location where there is an earthquake event within 3 s of the start of the earthquake's P-waves. The authors obtained data from three stations in Japan's Hi-net seismic network. They used their model to extract important waveforms using their characteristics to assess the parameters of the earthquake precisely. The 3 S-AE-CNN model separately predicted the earthquake's magnitude and location in terms of latitude and longitude. The earthquake characteristics obtained are transferred to an IoT system from the model, which alerts the unit responsible for taking action toward the earthquake event.

Table 4
Table showing some AI models and IoT platforms used for earthquake prediction.

Reference	AI model	IoT Platforms
Wu et al. (2021)	Multi- head CNN	MEMS
Clements (2021)	ML model	Arduino Cortex M4 microcontrollers
Zhai and Wang (2022)	SVM and KNN	Remote sensing based mobile computing
Khan et al. (2021)	NN	IoT acceleration nodes
Sreevidya et al. (2021)	SVR and XGB	IoT soil and terrain nodes
Koubâa et al. (2020)	CNN	UAV-based IoT
Abdalzaher et al. (2021b)	AU and CNN	Tmote sky
Tehseen et al. (2021)	FL	IoT gateway
Pughazhendhi et al. (2019)	RF	Mobile node- based feed processor
Khan and Kwon (2022)	CNN and LSTM	MEMS
Bassetti and Panizzi (2022)	CRNN	Raspberry Pi
Sarkar et al. (2021)	MLP	Strong motion nodes
Lee et al. (2019)	ANN	Acceleration sensors (ADXL355, LIS3DHH, MPU9250, and MMA8452)
Khan et al. (2020)	ANN	Smartphones
Fauvel et al. (2020)	RF, KNN, XGB, SVM,	GPS stations and seismometers
Falanga et al. (2022)	CNN	SSN/SOSA ontology

An Early Earthquake Warning System (EEWS) based on real-time response and integrated with IoT technology was developed by Clements (2021). Arduino Cortex M4 microcontroller and MEMS accelerometers were used to build the IoT network. The developed system decreased the detection latency and improved detection accuracy. The acceleration data used to build the model was from the deployed MEMS accelerometer nodes. Wu et al. (2021) developed an innovative seismic detection system called the CrowdQuake system based on a DL technique that combines with a dense IoT network to analyze large amounts of acceleration data. The IoT network was created from MEMS nodes as the foundation of the IoT network. The model proposed by the authors was evaluated on noise level, accuracy, and precision recall. The data for their model were obtained from the National Research Institute of Earth Science and Disaster Prevention (NIED). Furthermore, the authors stated that their model can detect an earthquake in few seconds and effectively manage data sent by 8000 IoT sensors. Pughazhendhi et al. (2019) proposed an IoT warning system for tsunami detection combined with an ML classification algorithm. Tsunami data from records from 2100 BC were used to develop the model. The parameters used to form the data to detect the earthquake were location, depth, magnitude and their model had high accuracy in its performance.

Khan and Kwon (2022) developed a DL algorithm model to detect P-waves in noisy environments. Their model monitors earthquake events using MEMS nodes to predict the presence of P-waves with high accuracy and faster detection time in a few seconds before the onset of strong shocks. Sarkar et al. (2021) proposed a model using a multilayer perceptron classifier that provided a severity-based warning system based on the probability that the intensity of the seismic events onsite would exceed the pre-trained PGA threshold associated with destructive force recorded on the Modified Mercalli Intensity scale. The classifier's supervised learning process was implemented using seismic features obtained from the strong motion signal after the onset of the P-waves. For the application, a stratified different feature window resampling method was used. Zhai and Wang (2022) developed a model for mitigating earthquake events and their effects by integrating mobile computing, remote sensing, ML models, SVM, and KNN. Entity categories, geographic connections, and entity names were the input features used for developing the model. The model's accuracy in predicting earthquakes was measured using the accuracy measure.

Khan et al. (2021) developed an IoT acceleration node to detect earthquakes. The authors reported on the use of seismic sensors for two methods which are a stand-alone method and a client-server method. The client-server method needs more computing power and a network framework however, it has more precision than the stand-alone method. The detection of simple earthquake events can be implemented using less powerful mobile nodes, but there are possibilities for false alarms. The authors stated that the solution to this problem is using a cooperative technique to detect earthquakes by using cell phones nearby on the same network, improving the method's accuracy. The method monitors seismic events caused by human activities, mechanical vibrations, or earthquakes. The mobile phones detect activities using the earthquake detection method, which has an NN, which helps to communicate with nearby devices. Sreevidya et al. (2021) developed a model for the prediction that uses IoT devices and ML to monitor geological landslide events. The model was trained for prediction using data obtained from geotechnical characteristics such as soil moisture, soil shear strength, rain intensity and terrain slope. Sensors were used to develop the

Table 5
Summary table of the different AI models used in literature as captured in this review, with details of data sources, performance and geological setting.

Reference	AI Method	Data Type	Results	Geological Setting
Essam et al. (2021)	ANN, RF	Ground motion parameters (Earthquake acceleration, depth, and velocity)	MSE = < e12 MAE = e 06, NSE >0.5	Terengganu,
Xiong et al. (2021)	Inverse Boosting Pruning Trees (IBPT)	Infrared and hyperspectral measurements	Precision = 80%	Global
Marhain et al. (2021)	SVM), boosted decision tree regression (BDTR), random forest regression (RFR) and multivariate adaptive regression spline (MAR Spline	Meteorological data	All the models used in have R^2 score has low values < 0.7 The observations is that most of the values lies <0.5 accuracy in terms of the R^2 score. BDTR model achieved R value for acceleration of 0.6516, 0.2596 RMSE and 0.1684 MAE HNE dataset and 0.5237 R value, 0.2592 RMSE and 0.1660 MAE for HNZ dataset	Terengganu,
Zhou et al., 2020	KNN, Haskell-based deterministic DCA (hDCA), Negative Selection Algorithm (NSA), Back Propagation Neural Network (BPNN), and SVM. The findings indicated that the earthquake prediction model based on ndDCA (EQP-ndDCA)	historical seismic data includes five features: event, data time, latitude, longitude and magnitude,	R2 score is > 80 for the best model and <50 for other models	Sichuan and surroundings
Bilal et al., 2022	We selected the GCNN [16], GCNN with batch normalization (BNGCNN), and GCNN with attention mechanism (GCNNAtt.) as baseline models to compare the results obtained from the proposed model.	Seismic datasets	RMSE. It achieved 1.62, 2.54, and 2.87 RMSE scores for Alaska events and 2.21, 2.43, and 2.66 for Japan events for small, medium, and large magnitude events	Alaska with sparse events distribution and Japan with dense events distribution;
Berhich et al. (2022)	recurrent neural network algorithms: Long Short Memory (LSTM), Gated Recurrent Network (GRU), and their hybrid model (LSTM-GRU).	Cluster of seismic dataset based on its geographical parameters (longitude and latitude)	Low MSE	Morocco, Japan, and Turkey
Turarbek et al. (2023)	Conv2D CNN (2-D CNN)	Seismic Data	63% accuracy, 82.4% precision, 62.7% recall, and f-score scores 83%	Kazakhstan
Bhatia et al. (2023)	BBM classification technique, ANFIS, C4.5 DT, SVM	Seismic Data	92.52% prediction accuracy using BBM classifier above other methods	
Gitis et al. (2021)	Method of the minimum area of alarm	GPS and seismological data	Probability	Japan and California
Abdalzaher et al. (20221a)	Ensemble ML algorithms (Logistic regression (LR), Linear and Quadratic Discriminant Analysis, Linear Support Vector Machine, Ridge Classifier, Gaussian Naive Bayes, AdaBoost, Gradient boosting (GB), Random Forest, K -Nearest Neighbors, CatBoost (CB)	Artificial seismic sources from explosives	>98.14% testing accuracy	Northern California
Tehseen et al. (2021)	Federated Learning (FL).	Seismic Data	88.87% prediction accuracy	Western Himalayas
Moustafa et al. (2021b).	DT, RFR, KNN, XGB, HGBR, ETR	Ground Vibrations from Blast	The R^2 of the DT has the highest performance = 0.9062 and lowest RMSE = 0.0663	Southeast of Helwan City, Egypt
Sadhukhan et al. (2023)	Long Short-Term Memory (LSTM), Bi-directional Long Short-Term Memory (Bi-LSTM), and self-attention-based transformer	Seismic indicators	LSTM Achieved MAE = 0.060, MSE = 0.006, log cosh = 0.042 and MSLE = 0.003	Japan, Indonesia, and the Hindu-Kush Karakoram Himalayan (HKKH)
Abdalzaher et al. (2023b)	2 S-ML-EIOS, XGB	Seismic Waveforms	98.59% R2 (i.e., 98.59% accuracy rate in predicting earthquake intensity), 96.7% F1, and 96.03% and 96.02% of both Kappa and MCC, respectively	Italy
Abdalzaher et al. (2022b)	XGB	earthquake (EQ) and quarry blasts (QBs)	100% discrimination between EQs and QBs	Northern Egypt

model's hardware and for obtaining data in real-time for soil and the terrain of the land.

Tehseen et al. (2021) researched earthquake prediction methods using FL. Their method was discovered to perform better than other ML earthquake models using the parameters efficiency, trustworthiness, and precision. The authors analyzed three local datasets to develop multiple ML data models. The local data models obtained were then integrated with the FedQuake algorithm on the central FL server through an IoT gateway to form global data models. The authors concluded that their model had a higher accuracy when multidimensional data in the Western Himalayas within a 100 km radius were used to evaluate the model. Bassetti and Panizzi (2022) proposed a method where computing is brought to the edge and used to detect earthquakes. The authors proposed method involved using detector nodes to observe and analyze data from the neighboring nodes. The model could preserve all the data locally and privately and withstand many nodes from failures and partial network outages. Twenty nodes were set up to test their model, each running on its device and linked to ten other nodes. Every 10 s, the number of detectors was counted.

Abdalzaher et al. (2023c) reported using ML and IoT to develop an EEWS in Smart Cities. The authors stated that the combination of ML and IoT could give accurate and timely data required for seismic activity analysis, which can be used to provide early warnings for the onsets of earthquakes. The authors also reported on various ML algorithms that can be employed to analyze seismic data, such as SVM, ANNs, and RFs. They also reported on the various types of sensors that can be used for data collection, including accelerometers, seismometers, and magnetometers, and the various communication protocols such as bluetooth, Wi-Fi, and Zigbee for the transmission of the obtained data. The authors presented a case study of how smart cities can benefit from implementing EEWS.

Mia et al. (2021) developed a smart and logical model for earthquake prediction that uses the Belief Rule-Based (BRB) system integrated with IoT. The algorithms developed can be used to predict earthquakes through the combination of changes in the behaviors of animals and environmental and chemical changes obtained from sensors as real-time inputs. The authors stated that the smart BRB system developed with IoT can detect potential earthquakes in a particular region using the parameters detected by the sensors. The authors compared the result of the model with other models, such as fuzzy-based models, and found that their model performed better in terms of accuracy.

4. Discussion

4.1. Combining conventional seismic monitoring tools with AI and IoT in earthquake prediction: challenges and opportunities

Significantly, conventional tools like seismometers, DAS systems, GPS etc have played a pivotal role in advancing our comprehension of geological contexts, conducting post-earthquake analyses, and monitoring various seismic parameters, including ground deformation, vibrations, and displacement waves (Allen et al., 2009; Allen and Melgar, 2019; Yoshimitsu et al., 2004; Allen and Kanamori, 2003; Waldhauser and Ellsworth, 2000; Gonzalez-Herraez et al., 2021; Shinohara et al., 2022; Fernández-Ruiz et al., 2020; Shan et al., 2017; Yoshimitsu et al., 2004). However, despite their historical significance in monitoring seismic activity and providing valuable retrospective data, these conventional tools grapple with certain limitations. Notably, they lack real-time earthquake prediction capabilities, face challenges related to temporal data resolution, exhibit uneven spatial coverage, and encounter difficulties in distinguishing seismic signals from environmental noise.

The advent of AI and IoT has substantially addressed some of these limitations associated with conventional methods. As evidenced in this review, AI methodologies have been instrumental in identifying intricate patterns and complex relationships within historical seismic data (Table 5). These approaches offer unique insights into diverse data types, outcomes, and geological locations worldwide, such as Alaska, Japan, Egypt, Sichuan, California, among others (Table 5). Each reviewed study contributes distinct perspectives on the challenges and potentials of deploying AI in earthquake forecasting. For example, Essam et al. (2021) and Xiong et al. (2021) highlight the efficacy of ground motion parameters and infrared/hyperspectral measurements, while Marhain et al. (2021) tackle challenges linked to meteorological data. Zhou et al. (2020) and Bilal et al., (2022) emphasize the significance of historical seismic data and advanced neural network architectures, respectively. Berhich et al. (2022) and Sadhukhan et al. (2023) explore capturing intricate seismic indicators across diverse geological environments through location-dependent predictions. Other methods focus on deciphering complex seismic patterns (Moustafa et al., 2021a), establishing robust early warning systems (Abdalzaher et al., 2022b; Abdalzaher et al., 2023b), and developing decentralized models (Tehseen et al., 2021).

For AI models for earthquake prediction, the selection of the problem type whether regression, time series analysis, or classification entwines intricately with the characteristics of the input data utilized. Innovative models such as EQP-ndDCA (Zhou et al., 2020), BDTR (Marhain et al., 2021), and IBPT (Xiong et al., 2021) showcase superior earthquake prediction performance compared to classical ML algorithms, highlighting the ongoing potential for innovation. At the other hand the IoT devices contribute to real-time monitoring by enabling seamless data transmission which can be used for the AI models Lu et al. (2020); Abdalzaher et al. (2021b); Esposito et al. (2022); Saini et al. (2022). The versatility of IoT enhances the accessibility and storage of data, creating a dynamic network for earthquake prediction (Lu et al. (2020); Abdalzaher et al. (2021b); Esposito et al. (2022); Saini et al. (2022). Despite the strides made by AI algorithms and IoT in earthquake prediction, several challenges persist, including computational complexity, data quality, interpretability, and uncertainties associated with seismic events. However, the integration of diverse datasets, including seismic, GPS, meteorological, and IoT sensor data etc, presents an opportunity to overcome limitations and develop more robust earthquake prediction models. Synthesizing traditional seismic monitoring methods with AI and IoT represents a transformative approach. The strengths of each method can compensate for the limitations of others, creating a synergistic framework for advancing earthquake prediction.

4.2. Significance of integrating hydrogeological data in constructing AI models for earthquake prediction

The challenge of predicting earthquake magnitude lies in the intricate and elusive nature of the underlying tectonics and hydrogeological property influence (Pwavodi and Doan, 2024). Within a specific geological setting, various factors contribute to the occurrence of earthquakes with different magnitudes (Saffer and Tobin, 2011; Kitajima and Saffer, 2012; Pwavodi and Doan, 2024; Pwavodi, 2023). Taking the Japan subduction zone as an example, which has experienced over 9 thousand earthquakes with magnitudes ranging from 1 to 9.5 Mw in the last 10 years, it becomes evident that distinct conditions and influences govern the generation of different magnitudes along fault zones (Magee and Zoback, 1993; Mazzotti et al., 2000; Pwavodi, 2023). These factors include tectonic influences, stress variations, fluid control, and fluid pressure (Uyeda and Kanamori, 1979; Kodaira et al., 2004; Saffer and Tobin, 2011; Kitajima and Saffer, 2012; Pwavodi and Doan, 2024; Pwavodi, 2023). Remarkably, current machine learning and AI models for earthquake prediction largely overlook hydrogeological property variations and their intricacies. The absence of detailed hydrogeological information in training datasets compromises the models' ability to discern the specific conditions leading to distinct earthquake magnitudes or even early warning signatures. Simply relying on secondary response measurements, like seismic data, meteorological data etc, without accounting for primary causative factors introduces a significant limitation. While the use of AI and IoT in earthquake forecasting and seismology is a burgeoning field, it is imperative for future research to integrate hydrogeological insights into predictive models. The integration of hydrogeological insights into predictive models is not just a refinement; it's a necessity. By bridging this gap, future research can forge more reliable, robust, and precise earthquake forecast models, propelling the field towards unprecedented advancements in seismic prediction accuracy. Since factors responsible for earthquake occurrence in different geological settings (subduction zones, transform faults, and divergent boundaries), we recommend a case-by-case approach that combines quantitative and qualitative data to unlock more accurate predictions, providing a more nuanced understanding of earthquake dynamics.

4.3. Challenges and future directions of artificial intelligence and IoT in earthquake prediction

In our comprehensive review, we've identified substantial progress and potential in employing AI and IoT for earthquake prediction. However, each method has its limitations, particularly in the integration of primary hydrogeological measurements into AI model training (see section 5.3). Monitoring hydrogeological data, such as elevated pore-fluid pressures, fluid flow, and temperature, is often very expensive. For instance, within the ocean drilling community, the Circulation Obviation Retrofit Kits (CORKs) are borehole observatory tools that provide direct in-situ measurements of these hydrogeological parameters over an extended period of time (months to years) (Becker and Davis, 2004; Kinoshita et al., 2018; Pwavodi 2023). The recorded data from CORKs have been explored as precursors for detecting phenomena preceding significant earthquakes, slow slips, and tremors (Becker and Davis, 2004; Kinoshita et al., 2018; Pwavodi 2023). Evidence suggests that abnormal changes in pore-fluid pressures, fluid flow, fluid chemistry, and temperature data are correlated with the occurrence of slow slips, tremors, and large-magnitude earthquakes (Becker and Davis, 2004; Kinoshita et al., 2018).

However, in some cases, these data are not transmitted in real-time to operators but rather stored internally within the device. This stands in contrast to IoT systems that provide real-time changes during their installation period. Various instruments similar to the CORK are likely used within the scientific community. Hence, an opportunity exists to develop tools considering the strengths and weaknesses of each method to enhance earthquake prediction in time and space. Specifically designed IoT devices can be integrated into tools like the CORK, enabling real-time transmission of hydrogeological measurements (elevated pore-fluid pressures, fluid flow, fluid chemistry, and temperature variation) influencing earthquakes. This real-time data can be used alongside seismic data, GPS, meteorological data, etc., to construct predictive AI models. We propose a detailed incorporation (Fig. 9) of all necessary components into one system housing geophysical tools, IoT, and AI algorithms. The system aims to enable AI algorithms to independently recognize complex patterns and relationships in historical and real-time data, providing real-time earthquake predictions. This proposition aims to address challenges related to early warning systems, spatial data, data fusion and integration, and real-time prediction.

4.4. Relevance to practice

AI and IoT techniques are currently changing the landscape of earthquake prediction. Despite the fact that the technology is not yet at its peak due to several factors and limitations, however, progress have been made compared to last decades. Thus, this review updated and synthesized the evidence base on the role of AI and IoT in predicting earthquakes using seismic data. Thus, this review identifies that.

- Seismologist need to collaborate more with computer experts in and get involved in the implementation and evaluation of AI/IoT frameworks in order to ensure it is developed and applied appropriately.
- Accurate and reliable prediction using these frameworks require the use of good quality and digital data that can support the models.
- There is need to develop and update a database of seismic data using multiplex datasets generated using different devices.
- Rigorous and interdisciplinary practical researches are needed in order to determine the efficacy of these frameworks for prediction of real-world events and improving decision making.

4.5. Limitations

Despite the fact that this review covers several topics and sub-topics and hyphenate between AI, IoT and earthquake prediction using seismic data. The review does not cover all the techniques that can be used to determine or predict earthquakes. However, the search criteria focus on only Earthquakes, AI and IoT, other computational approach are not included. Consequently, alternate sources such as online resources, articles written in other languages, articles without Doi numbers were not included, meaning that some important literature may have been missed. No formal critical appraisal of retrieved studies was undertaken, so the strength of evidence on these frameworks remains unknown, which may reduce the quality of the review findings.

5. Conclusion

Accurate earthquake prediction is challenging despite the advances in science and technology. Scientists have yet to develop a system that can exactly predict when earthquakes are going to occur, their specific epicentre locations, and their magnitude. However, in this review we presented a comprehensive exploration of earthquake prediction methodologies, scrutinizing advances in seismic monitoring, the use of seismometers, distributed acoustic sensing (DAS), satellite data, global position system (GPS), InSAR and the most recent advances in AI, ML, and IoT. Seismic devices, including seismometers and satellite-based technologies, have contributed significantly to monitoring seismic activity. However, pinpointing precise predictions remains elusive. The integration of AI and ML, showcased through a diverse array of algorithms, unveils promising strides in leveraging historical seismic data for predictive modeling. Despite notable successes, each algorithm presents inherent limitations, emphasizing the nuanced challenges associated with achieving absolute predictive accuracy. We highlighted several limitations with the AI and ML algorithm in terms of the unavailability

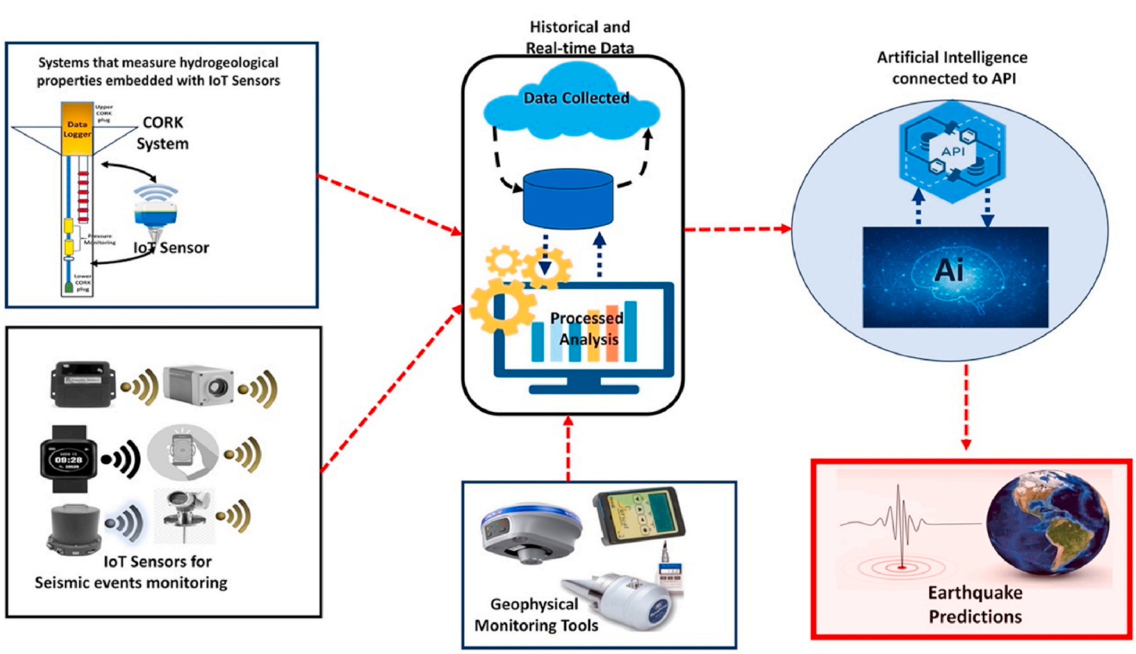

Fig. 9. Proposed integrated system architecture with multiple data sources used for AI and ML Earthquake model Prediction.

of diverse spatial data, computational inefficiency etc., Crucially, none of the AI and ML models considered primary hydrogeological factors influencing earthquakes in different geological settings. These hydrogeological factors when considered as part of input datasets for training and building AI and ML models could further improve the earthquake prediction accuracy. In conclusion the confidence level for earthquake prediction can significantly be improved, by gathering, combining and analysing different data from a broad variety of sources (IoT devices and geophysical tools), developing accurate algorithms, models and implement sound technical concepts.

CRediT authorship contribution statement

Joshua Pwavodi: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abdullahi Umar Ibrahim:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Pwadubashiyi Coston Pwavodi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology. **Fadi Al-Turjman:** Writing – review & editing, Writing – original draft, Supervision. **Ali Mohand-Said:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abdalzaher, M.S., Moustafa, S.S., Abd-Elnaby, M., Elwekeil, M., 2021a. Comparative performance assessments of machine-learning methods for artificial seismic sources discrimination. IEEE Access 9, 65524–65535. https://doi.org/10.1109/ACCESS.2021.3076119.

Abdalzaher, M.S., Soliman, M.S., El-Hady, S.M., Benslimane, A., Elwekeil, M., 2021b. A deep learning model for earthquake parameters observation in IoT system-based earthquake early warning. IEEE Internet Things J. 9 (10), 8412–8424. https://doi.org/10.1109/JIOT.2021.3114420.

Abdalzaher, M.S., Elsayed, H.A., Fouda, M.M., 2022. Employing remote sensing, data communication networks, ai, and optimization methodologies in seismology. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 15, 9417–9438. https://doi.org/10.1109/JSTARS.2022.3216998.

Abdalzaher, M.S., Moustafa, S.S., Hafiez, H.A., Ahmed, W.F., 2022b. An optimized learning model augment analyst decisions for seismic source discrimination. IEEE Trans. Geosci. Rem. Sens. 60, 1–12. https://doi.org/10.1109/TGRS.2022.3208097.

Abdalzaher, M.S., Krichen, M., Yiltas-Kaplan, D., Ben Dhaou, I., Adoni, W.Y.H., 2023a. Early detection of earthquakes using IoT and cloud infrastructure: a survey. Sustainability 15 (15), 11713. https://doi.org/10.3390/su151511713.

Abdalzaher, M.S., Soliman, M.S., El-Hady, S.M., 2023b. Seismic intensity estimation for earthquake early warning using optimized machine learning model. IEEE Trans. Geosci. Rem. Sens. https://doi.org/10.1109/TGRS.2023.3296520.

Abdalzaher, M.S., Elsayed, H.A., Fouda, M.M., Salim, M.M., 2023c. Employing machine learning and IoT for earthquake early warning system in smart cities. Energies 16 (1), 495. https://doi.org/10.3390/en16010495.

Al Banna, M.H., Taher, K.A., Kaiser, M.S., Mahmud, M., Rahman, M.S., Hosen, A.S., Cho, G.-H., 2020. Application of artificial intelligence in predicting earthquakes: state-of-the-art and future challenges. IEEE Access 8, 192880–192923. https://doi.org/10.1109/ACCESS.2020.3029859.

Al-Turjman, F., Alturjman, S., 2018. Context-sensitive access in industrial internet of things (IIoT) healthcare applications. IEEE Trans. Ind. Inf. 14 (6), 2736–2744. https://doi.org/10.1109/TII.2018.2808190.

Alessio, M., Allegri, L., Bella, F., Della Monica, G., Ermini, A., Improta, S., Biagi, P., 1980. Study of some precursory phenomena for the umbria earthquake of september 19, 1979. Il Nuovo Cimento C 3, 589–600. https://doi.org/10.1007/BF02507185.

Allegri, L., Bella, F., Della Monica, G., Ermini, A., Improta, S., Sgrigna, V., Biagi, P., 1983. Radon and rilt anomalies detected before the Irpinia (south Italy) earthquake of november 23, 1980 at great distances from the epicenter. Geophys. Res. Lett. 10 (4), 269–272. https://doi.org/10.1029/GL010i004p00269.

Allen, R.M., Kanamori, H., 2003. The potential for earthquake early warning in Southern California. Science 300 (5620), 786–789. https://doi.org/10.1126/science.1080912.

Allen, R.M., Melgar, D., 2019. Earthquake early warning: advances, scientific challenges, and societal needs. Annu. Rev. Earth Planet Sci. 47 (1), 361–388. https://doi.org/10.1146/annurev-earth-053018-060457.

Allen, R.M., Gasparini, P., Kamigaichi, O., Bose, M., 2009. The status of earthquake early warning around the world: an introductory overview, 09 Seismol Res. Lett. 80 (5), 682–693. https://doi.org/10.1785/gssrl.80.5.682.

Alzubi, J., Nayyar, A., Kumar, A., 2018. Machine learning from theory to algorithms: an overview. J. Phys. Conf. 1142 (1), 012012 https://doi.org/10.1088/1742-6596/1142/1/012012.

Aman, A.H.M., Yadegaridehkordi, E., Attarbashi, Z.S., Hassan, R., Park, Y.-J., 2020. A survey on trend and classification of internet of things reviews. IEEE Access 8, 111763–111782. https://doi.org/10.1109/ACCESS.2020.3002932.

Ando, M., 1975. Source mechanisms and tectonic significance of historical earthquakes along the Nankai Trough, Japan. Tectonophysics 27. https://doi.org/10.1016/0040-1951(75)90102-X, 119-110.

Arpat, E., Şaroğlu, F., 1975. Türkiyédeki bazıönemli genç tektonik olaylar. Turk. Jeol. Kurumu Bul. 18, 91–101.

Arpat, E., Şaroğlu, F., 1972. The East Anatolian fault system; thoughts on its development. Bull. Miner. Res. Explor. 78.

Aslam, B., Zafar, A., Khalil, U., Azam, U., 2021a. Seismic activity prediction of the northern part of Pakistan from novel machine learning technique. J. Seismol. 1–14.

Aslam, B., Zafar, A., Qureshi, U., Khalil, U., 2021b. Seismic investigation of the northern part of Pakistan using the statistical and neural network algorithms. Environ. Earth Sci. 80 (2), 1–18. https://doi.org/10.1007/s12665-020-09348-x.

Atzori, L., Iera, A., Morabito, G., Nitti, M., 2012. The social internet of things (SIoT) when social networks meet the internet of things: concept, architecture and network characterization. Comput. Network. 56 (16), 3594–3608. https://doi.org/10.1016/j.comnet.2012.07.010.

Azam, F., Sharif, M., Yasmin, M., Mohsin, S., 2014. Artificial intelligence based techniques for earthquake prediction: a review. Sci. Int. 26 (4), 1495–1502.

Bassetti, E., Panizzi, E., 2022. Earthquake detection at the edge: IoT crowdsensing network. Information 13 (4), 195. https://doi.org/10.3390/info13040195.

Becker, K., Davis, E.E., 2004. A review of CORK designs and operations during the Ocean Drilling Program. Proc. IODP| 301, 2.

Berardino, P., Fornaro, G., Lanari, R., Sansosti, E., 2002. A new algorithm for surface deformation monitoring based on small baseline differential sar interferograms. IEEE Trans. Geosci. Rem. Sens. 40 (11), 2375–2383. https://doi.org/10.1109/TGRS.2002.803792.

Berhich, A., Belouadha, F.-Z., Kabbaj, M.I., 2022. A location-dependent earthquake prediction using recurrent neural network algorithms. Soil Dynam. Earthq. Eng. 161, 107389 https://doi.org/10.1016/j.soildyn.2022.107389.

Bhatia, M., Ahanger, T.A., Manocha, A., 2023. Artificial intelligence based realtime earthquake prediction. Eng. Appl. Artif. Intell. 120, 105856 https://doi.org/10.1016/j.engappai.2023.105856.

Bilal, M.A., Ji, Y., Wang, Y., Akhter, M.P., Yaqub, M., 2022. An early warning system for earthquake prediction from seismic data using batch normalized graph convolutional neural network with attention mechanism (BNGCNNATT). Sensors 22 (17), 6482. https://doi.org/10.3390/s22176482.

Boatwright, J., Seekins, L.C., 2011. Regional spectral analysis of three moderate earthquakes in northeastern North America. Seismological Soc. Am. 101, 1769–1782. https://doi.org/10.1785/0120100225.

Boccadoro, P., Montaruli, B., Grieco, L.A., 2019. Quakesense, a LoRa-compliant earthquake monitoring open system. In: Proceedings of the 2019 IEEE/ACM 23rd International Symposium on Distributed Simulation and Real Time Applications (DS-RT), pp. 1–8. Cosenza, Italy, 7–9 October.

Bondàr, I., Engdahl, E.R., Villasenõr, A., Harris, J., Storchak, D., 2015. Isc-gem: global instrumental earthquake catalogue (1900–2009), ii. location and seismicity patterns. Phys. Earth Planet. In. 239, 2–13. https://doi.org/10.1016/j.pepi.2014.06.002 (ISC-GEM Catalogue).

Bowen, H., Jacka, M., Van Ballegooy, S., Sinclair, T., Cowan, H., 2012. Lateral spreading in the canterbury earthquakes–observations and empirical prediction methods. In: Proceedings, 15th World Conference on Earthquake Engineering.

Bürgmann, R., Rosen, P.A., Fielding, E.J., 2000. Synthetic aperture radar interferometry to measure earth's surface topography and its deformation. Annu. Rev. Earth Planet Sci. 28 (1), 169–209. https://doi.org/10.1146/annurev.earth.28.1.169.

Chen, C.-C., Rundle, J.B., Holliday, J.R., Nanjo, K.Z., Turcotte, D.L., Li, S.-C., Tiampo, K. F., 1999. The 1999 Chi-Chi, Taiwan, earthquake as a typical example of seismic activation and quiescence. Geophys. Res. Lett. 32 (22) https://doi.org/10.1029/2005GL023991.

Cicerone, R.D., Ebel, J.E., Britton, J., 2009. A systematic compilation of earthquake precursors. Tectonophysics 476 (3–4), 371–396. https://doi.org/10.1016/j.tecto.2009.06.008.

Clements, T., 2021. Earthquake detection with tinyml, 12 Proc. AGU Fall Meeting Abstracts 2021, S15A–S229. New Orleans, LA, USA.

Curilem, M., Vergara, J., Martin, C.S., Fuentealba, G., Cardona, C., Huenupan, F., et al., 2014. Pattern recognition applied to seismic signals of the llaima volcano (Chile): an analysis of the events' features. J. Volcanol. Geoth. Res. 282, 134–147. https://doi.org/10.1016/j.jvolgeores.2014.06.004.

Dal Zilio, L., Ampuero, J.P., 2023. Earthquake doublet in Turkey and Syria. Commun. Earth Environ. 4, 71. https://doi.org/10.1038/s43247-023-00747-z.

Davis, D., Suppe, J., Dahlen, F.A., 1983. Mechanics of fold-and- thrust belts and accretionary wedges. J. Geophys. Res. 88 (B2), 1153–1172. https://doi.org/10.1029/JB088iB02p01153.

Delsemme, J., Smith, A.T., 1979. Spectral analysis of earthquake migration in South America. In: Wyss, M. (Ed.), Earthquake Prediction and Seismicity Patterns. Birkhäuser Basel, Basel, pp. 1271–1285. https://doi.org/10.1007/978-3-0348-6430-5.10.

Dessa, S.O., Kaneda, Y., 2004. Deep seismic imaging of the eastern Nankai trough, Japan, from multifold ocean bottom seismometer data by combined travel time tomography

and prestack depth migration. J. Geophys. Res. 109, B02111 https://doi.org/10.1029/2003JB002689.
Didier, M., Feigl, K., Rossi, M., Adragna, F., 1994. Radar interferometric mapping of deformation in the year after the lander's earthquake. Nature 369, 227–230. https://doi.org/10.1038/369227a0.
Dong, L., Shan, J., 2013. A comprehensive review of earthquake-induced building damage detection with remote sensing techniques. ISPRS J. Photogrammetry Remote Sens. 84, 85–99. https://doi.org/10.1016/j.isprsjprs.2013.06.011.
Elkhodr, M., Shahrestani, S., Cheung, H., 2016. The Internet of Things: New Interoperability, Management and Security Challenges. *arXiv preprint arXiv:1604.04824*.
Esposito, M., Palma, L., Belli, A., Sabbatini, L., Pierleoni, P., 2022. Recent advances in internet of things solutions for early warning systems: a review. Sensors 22 (6), 2124. https://doi.org/10.3390/s22062124.
Essam, Y., Kumar, P., Ahmed, A.N., Murti, M.A., El-Shafie, A., 2021. Exploring the reliability of different artificial intelligence techniques in predicting earthquake for Malaysia. Soil Dynam. Earthq. Eng. 147, 106826 https://doi.org/10.1016/j.soildyn.2021.106826.
Falanga, M., De Lauro, E., Petrosino, S., Rincon-Yanez, D., Senatore, S., 2022. Semantically enhanced IoT-oriented seismic event detection: an application to colima and vesuvius volcanoes. IEEE Internet Things J. 9, 9789–9803. https://doi.org/10.1109/JIOT.2022.3148786.
Fauvel, K., Balouek-Thomert, D., Melgar, D., Silva, P., Simonet, A., Antoniu, G., et al., 2020. A distributed multi-sensor machine learning approach to earthquake early warning. Proc. AAAI Conf. Artif. Intell. 34, 403–411. https://doi.org/10.1609/aaai.v34i01.5376. New York, NY, USA.
Fernández-Ruiz, M.R., Soto, M.A., Williams, E.F., Martin-Lopez, S., Zhan, Z., GonzalezHerraez, M., Martins, H.F., 2020. Distributed acoustic sensing for seismic activity monitoring. APL Photonics 5 (3), 030901. https://doi.org/10.1063/1.5139602.
Fischer, J., Kühnlenz, F., Ahrens, K., Eveslage, I., 2009. Model-based development of self-organizing earthquake early warning systems. Simul. Notes Eur. 19, 9–20.
Garavaglia, M., Braitenberg, C., Zadro, M., 1998. Radon monitoring in a cave of north-eastern Italy. Phys. Chem. Earth 23 (9–10), 949–952. https://doi.org/10.1016/S0079-1946(98)00125-6.
Gitis, V., Derendyaev, A., Petrov, K., 2021. Analyzing the performance of GPS data for earthquake prediction. Rem. Sens. 13 (9), 1842. https://doi.org/10.3390/rs13091842.
Gonzalez-Herraez, M., Fernandez-Ruiz, M.R., Magalhaes, R., Costa, L., Martins, H.F., Becerril, C., et al., 2021. Distributed acoustic sensing for seismic monitoring. In: Optical Fibre Communication Conference (Ofc. Optica Publishing Group, p. 2021. https://doi.org/10.1364/OFC.2021.Tu1L.2. Tu1L.2).
Gowda, V., Sridhara, S., Naveen, K., Ramesha, M., Pai, G., 2020. Internet of things: internet revolution, impact, technology road map and features. Adv. Math.: Sci. J. 9 (7), 4405–4414. https://doi.org/10.37418/amsj.9.7.11.
Hamdy, O., Gaber, H., Abdalzaher, M.S., Elhadidy, M., 2022. Identifying exposure of urban area to certain seismic hazard using machine learning and GIS: a case study of greater Cairo. Sustainability 14 (17), 10722. https://doi.org/10.3390/su141710722.
Hamilton, Eric, 2018. What Is Edge Computing: the Network Edge Explained. cloudwards.net. Retrieved 2019-05-14.
Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction, second ed. Springer. https://doi.org/10.1007/978-0-387-84858-7.
Hauksson, E., Goddard, J.G., 1981. Radon earthquake precursor studies in Iceland. J. Geophys. Res. Solid Earth 86 (B8), 7037–7054. https://doi.org/10.1029/JB086iB08p07037.
Hillier, A.J.R., Makarovaite, V., Gourlay, C.W., Holder, S.J., Batchelor, J.C., 2019. A passive UHF RFID dielectric sensor for aqueous electrolytes. IEEE Sensor. J. 19, 5389–5395.
Hooper, A., Bekaert, D., Spaans, K., Arıkan, M., 2012. Recent advances in SAR interferometry time series analysis for measuring crustal deformation. Tectonophysics 514–517, 1–13. https://doi.org/10.1016/j.tecto.2011.10.013.
Igarashi, G., Wakita, H., 1990. Groundwater radon anomalies associated with earthquakes. Tectonophysics 180 (2–4), 237–254. https://doi.org/10.1016/0040-1951(90)90311-U.
Jamshed, M.A., Ali, K., Abbasi, Q.H., Imran, M.A., Ur-Rehman, M., 2022. Challenges, applications, and future of wireless sensors in internet of things: a review. IEEE Sensor. J. 22 (6), 5482–5494. https://doi.org/10.1109/JSEN.2022.3148128, 15 March15.
Jordan, M.I., Mitchell, T.M., 2015. Machine learning: trends, perspectives, and prospects. Science 349 (6245), 255–260. https://doi.org/10.1126/science.aaa8415.
Kamei, R., Pratt, R.G., Tsuji, T., 2013. On acoustic waveform tomography of wide-angle obs data-strategies for pre-conditioning and inversion. Geophys. J. Int. 194, 1250–1280. https://doi.org/10.1093/gji/ggt165.
Kanamori, H., 1972. Tectonic implications of the 1943 Tonankai and the 1946 nankaido earthquakes. Phys. Earth Planet. In. 5, 129–139. https://doi.org/10.1016/0031-9201(72)90082-9.
Kanamori, H., 1977. The energy release in great earthquakes. J. Geophys. Res. 82 (20), 2981–2987. https://doi.org/10.1029/JB082i020p02981.
Kanamori, H., 2005. Real-time seismology and earthquake damage mitigation. Annu. Rev. Earth Planet Sci. 33, 195–214. https://doi.org/10.1146/annurev.earth.33.092203.122626.
Kanamori, H., Brodsky, E.E., 2004. The physics of earthquakes. Rep. Prog. Phys. 67 (8), 1429–1496. https://doi.org/10.1088/0034-4885/67/8/r03.
Khan, I., Kwon, Y.W., 2022. P-detector: real-time p-wave detection in a seismic waveform recorded on a low-cost MEMS accelerometer using deep learning. Geosci. Rem. Sens. Lett. IEEE 19, 1–5. https://doi.org/10.1109/LGRS.2022.3161017.
Khan, I., Choi, S., Kwon, Y.W., 2020. Earthquake detection in a static and dynamic environment using supervised machine learning and a novel feature extraction method. Sensors 20, 800. https://doi.org/10.3390/s20030800.
Khan, I., Pandey, M., Kwon, Y.W., 2021. An earthquake alert system based on a collaborative approach using smart devices. In: Proceedings of the 2021 Ieee/acm 8th International Conference on Mobile Software Engineering and Systems (Mobilesoft), pp. 61–64. https://doi.org/10.1109/MobileSoft52590.2021.00014. Madrid, Spain.
Khodadadi, F., Dastjerdi, A., Buyya, R., 2016. Internet of things: an overview. Internet of Things 3–27. https://doi.org/10.1016/B978-0-12-805395-9.00001-0.
Kinoshita, C., Saffer, D., Kopf, A., Roesner, A., Wallace, L.M., Araki, E., et al., 2018. Changes in physical properties of the Nankai Trough Megasplay Fault induced by earthquakes, detected by continuous pressure monitoring. J. Geophys. Res. Solid Earth 123 (2), 1072–1088.
Kitajima, H., Saffer, D.M., 2012. Elevated pore pressure and anomalously low stress in regions of low frequency earthquakes along the Nankai Trough subduction megathrust. Geophys. Res. Lett. 39 (23), 1–5. https://doi.org/10.1029/2012GL053793.
Kodaira, S., Iidaka, T., Kato, A., Park, J.O., Iwasaki, T., Kaneda, Y., 2004. High pore fluid pressure may cause silent slip in the Nankai Trough. Science 304 (5675), 1295–1298. https://doi.org/10.1126/science.1096535.
Kok, J.N., Boers, E.J., Kosters, W.A., Van der Putten, P., Poel, M., 2009. Artificial intelligence: definition, trends, techniques, and cases. Artif. Intell. 1, 270–299.
Koubâa, A., Ammar, A., Alahdab, M., Kanhouch, A., Azar, A.T., 2020. Deepbrain: experimental evaluation of cloud-based computation offloading and edge computing in the internet-of-drones for deep learning applications. Sensors 20 (18), 5240. https://doi.org/10.3390/s20185240.
Laasri, H.A., Akhouayri, E.-S., Agliz, D., Zonta, D., Atmani, A., 2015. A fuzzy expert system for automatic seismic signal classification. Expert Syst. Appl. 42, 1013–1027.
Lay, T., 2016. Great Earthquakes on Plate Boundaries. Oxford University Press. https://doi.org/10.1093/acrefore/9780199389407.013.32.
Lay, T., Kanamori, H., 1981. An asperity model of large earthquake sequences. In: Simpson, D.W., Richards, P.G. (Eds.), Earthquake Prediction. American Geophysical. https://doi.org/10.1029/ME004p0579.
Lay, T., Kanamori, H., Ruff, L., 1982. The asperity model and the nature of large subduction zone earthquakes. Earthq. Pred. Res. 1 (1), 3–71.
Le Breton, M., Liébault, F., Baillet, L., Charléty, A., Larose, É., Tedjini, S., 2022. Dense and long-term monitoring of earth surface processes with passive RFID—a review. Earth Sci. Rev. 234, 104225.
Lee, J., Khan, I., Choi, S., Kwon, Y.-W., 2019. A smart IoT device for detecting and responding to earthquakes. Electronics 8 (12), 1546. https://doi.org/10.3390/electronics8121546.
Li, P., Chen, Z., Yang, L., Zhang, Q., Deen, M.J., 2017. Deep convolutional computation model for feature learning on big data in internet of things. IEEE Trans. Ind. Inf. 14 (2), 790–798. https://doi.org/10.1109/TII.2017.2739340.
Li, M., Pranger, C., van Dinther, Y., 2022. Characteristics of earthquake cycles: a cross-dimensional comparison of 0d to 3d numerical models. J. Geophys. Res. Solid Earth 127 (8), e2021JB023726. https://doi.org/10.1029/2021JB023726.
Lim, W.-Y.B., Luong, N.C., Hoang, D.T., Jiao, Y., Liang, Y.-C., Yang, Q., et al., 2020. Federated learning in mobile edge networks: a comprehensive survey. IEEE Commun. Surv. & Tutorials 22 (3), 2031–2063. https://doi.org/10.1109/COMST.2020.2986024.
Liu, Y., Rice, J.R., 2007. Spontaneous and triggered aseismic deformation transients in a subduction fault model. J. Geophys. Res. Solid Earth 112 (9), 1–23. https://doi.org/10.1029/2007JB004930.
Lu, Y., Huang, X., Dai, Y., Maharjan, S., Zhang, Y., 2020. Blockchain and federated learning for privacy-preserved data sharing in industrial IoT. IEEE Trans. Ind. Inf. 16 (6), 4177–4186. https://doi.org/10.1109/TII.2019.2942190.
Magee, M.E., Zoback, M.D., 1993. Evidence for a weak interplate thrust fault along the northern Japan subduction zone and implications for the mechanics of thrust faulting and fluid expulsion. Geology 21 (9), 809–812. https://doi.org/10.1130/0091-7613(1993)021⟨0809:EFAWIT⟩2.3.CO;2.
Marhain, S., Ahmed, A.N., Murti, M.A., Kumar, P., El-Shafie, A., 2021. Investigating the application of artificial intelligence for earthquake prediction in Terengganu. Nat. Hazards 108, 977–999. https://doi.org/10.1007/s11069-021-04716-7.
Massonnet, D., Feigl, K.L., 1998. Radar interferometry and its application to changes in the earth's surface. Rev. Geophys. 36 (4), 441–500. https://doi.org/10.1029/97RG03139.
Mazzotti, S., Pichon, X.L., Henry, P., Miyazaki, S.I., 2000. Full interseismic locking of the Nankai and Japan -West Kurile subduction zones: an analysis of uniform elastic strain accumulation in Japan constrained by permanent GPS, 6 J. Geophys. Res. Solid Earth 105, 13159–13177. https://doi.org/10.1029/2000jb900060.
McCarthy, J., Minsky, M.L., Rochester, N., Shannon, C.E., 2006. A proposal for the Dartmouth summer research project on artificial intelligence, august 31, 1955. AI Mag. 27 (4) https://doi.org/10.1609/aimag.v27i4.1904, 12–12.
Mia, M.M., Al Hasan, A., Atiqur, R., Mustafa, R., 2021. An internet of things belief rule base smart system to predict earthquake. Int. J. Reconfigurable Embed. Syst. 10 (2), 149. https://doi.org/10.11591/ijres.v10.i2.pp149-156.
Mirrashid, M., 2014. Earthquake magnitude prediction by adaptive neuro-fuzzy inference system (Anfis) based on fuzzy c-means algorithm. Nat. Hazards 74 (3), 1577–1593. https://doi.org/10.1007/s11069-014-1264-7.
Moiş, G.D., Sanislav, T., Folea, S.C., Zeadally, S., 2018. Performance evaluation of energy-autonomous sensors using power-harvesting beacons for environmental

monitoring in internet of things (IoT). Sensors 18, 1709. https://doi.org/10.3390/s18061709.

Mora, H., Signes-Pont, M.T., Gil, D., Johnsson, M., 2018. Collaborative working architecture for IoT-based applications. Sensors 18 (6), 1676. https://doi.org/10.3390/s18061676.

Morales, E.F., Escalante, H.J., 2022. A brief introduction to supervised, unsupervised, and reinforcement learning. In: Biosignal Processing and Classification Using Computational Learning and Intelligence. Academic Press, pp. 111–129. https://doi.org/10.1016/B978-0-12-820125-1.00017-8.

Mosher, S.G., Audet, P., 2020. Automatic detection and location of seismic events from time-delay projection mapping and neural network classification. J. Geophys. Res. Solid Earth 125 (10), e2020JB019426. https://doi.org/10.1029/2020JB019426.

Moustafa, S.S., Abdalzaher, M.S., Khan, F., Metwaly, M., Elawadi, E.A., Al-Arifi, N.S., 2021a. A quantitative site-specific classification approach based on affinity propagation clustering. IEEE Access 9, 155297–155313. https://doi.org/10.1109/ACCESS.2021.3128284.

Moustafa, S.S., Abdalzaher, M.S., Yassien, M.H., Wang, T., Elwekeil, M., Hafiez, H.E.A., 2021b. Development of an optimized regression model to predict blast-driven ground vibrations. IEEE Access 9, 31826–31841. https://doi.org/10.1109/ACCESS.2021.3059018.

Moustafa, S.S., Mohamed, G.E.A., Elhadidy, M.S., Abdalzaher, M.S., 2023. Machine learning regression implementation for high-frequency seismic wave attenuation estimation in the Aswan Reservoir area, Egypt. Environ. Earth Sci. 82 (12), 307. https://doi.org/10.1007/s12665-023-10947-7.

Ni, S, Sun, H, Somerville, P, Yuen, DA, Milliner, C, Wang, H, Zhou, J, Cui, Y., 2023. Complexities of the Turkey-Syria doublet earthquake sequence. Innovation Camb 4 (3), 100431. https://doi.org/10.1016/j.xinn.2023.100431.

Pacheco, J.F., Sykes, L.R., Scholz, C.H., 1993. Nature of seismic coupling along simple plate boundaries of the subduction type. J. Geophys. Res. 98 (B8) https://doi.org/10.1029/93jb00349.

Panchal, H., Saraf, A., Das, J., Dwivedi, D., 2022. Satellite based detection of pre-earthquake thermal anomaly, co-seismic deformation and source parameter modelling of past earthquakes. Nat. Haz. Res. 2 (4), 287–303. https://doi.org/10.1016/j.nhres.2022.12.001.

Papastefanou, C., Manolopoulou, M., Savvides, E., Charalambous, S., 1989. Radon monitoring at the Stivos fault following the m/sub l/= 6. 5 earthquake which occurred at Thessaloniki, Greece on 20 June 1978. Nucl. Geophys. 3 (1).

Pirmagomedov, R., Blinnikov, M., Amelyanovich, A., Glushakov, R., Loskutov, S., Koucheryavy, A., et al., 2018. IoT based earthquake prediction technology. Internet of things, smart spaces, and next generation networks and systems: 18th Int. Conf., New2an 2018, and 11th Conf. 18, 535–546. Rusmart 2018, St. Petersburg, Russia, August 27–29, 2018, proceedings.

Pourabdollahian, G., Gole, J., Eisenträger, M., Giuffrida, M., 2022. Understanding Cloud-Edge-IoT: Challenges and Opportunities—Webinar Slides. Zenodo, Geneva, Switzerland.

Pughazhendhi, G., Raja, A., Ramalingam, P., Elumalai, D., 2019. Earthosys—tsunami prediction and warning system using machine learning and IoT. In: Proceedings of the International Conference on Computational Intelligence and Data Engineering, pp. 103–113. Manchester, UK.

Pwavodi, J.T., 2023. Intégration des données de géophysique en forage et des propriétés pétrophysiques sur carottes pour modéliser les propriétés hydrogéologiques de la zone de subduction de Nankai. Doctoral dissertation, Université Grenoble Alpes [2019-2023]).

Pwavodi, J., Doan, M.-L., 2021. Hydrogeological properties at the toe of the Nankai accretionary prism, using borehole geophysical and petrophysical data within hole C0024a, expedition 358 of IODP – nantroseize project. Sixth Int. Conf. Eng. Geophys., virtual 150–154. https://doi.org/10.1190/iceg2021-040.1, 25–28 October 2021.

Pwavodi, J., Doan, M.-L., 2022. Direct evidence of high pore pressure at the toe of the Nankai accretionary prism. Authorea Preprints. https://doi.org/10.5194/egusphere-egu22-1679.

Pwavodi, J., Doan, M.L., 2024. Direct assessment of the hydraulic structure of the plate boundary at the toe of the Nankai accretionary prism. Geophys. J. Int. 236 (2), 1125–1138. https://doi.org/10.1093/gji/ggad473.

Pwavodi, J., Kelechi, I.N., Angalabiri, P., Emeremgini, S.C., Oguadinma, V.O., 2023. Pore pressure prediction in offshore Niger Delta using data-driven approach: implications on drilling and reservoir quality. Energy Geosci. 4 (3), 100194 https://doi.org/10.1016/j.engeos.2023.100194.

Ray, P., Mukherjee, M., Shu, L., 2017. Internet of Things for Disaster Management. https://doi.org/10.1016/j.tecto.2011.10.013.

Riggio, A., Santulin, M., et al., 2015. Earthquake forecasting: a review of radon as seismic precursor. Bollettino Di Geofisica Teorica e Applicata 56 (2), 95–114.

Rose, K., Eldridge, S., Chapin, L., 2015. The internet of things: an overview. The Internet Soc. (ISOC) 80, 1–50.

Ross, Z.E., Ben-Zion, Y., White, M.C., Vernon, F.L., 2016. Analysis of earthquake body wave spectra for potency and magnitude values: implications for magnitude scaling relations, 09 Geophys. J. Int. 207 (2), 1158–1164. https://doi.org/10.1093/gji/ggw327.

Russell, S., Norvig, P., 2010. Artificial Intelligence: A Modern Approach, third ed. Prentice-Hall, Upper Saddle River.

Sadhukhan, B., Chakraborty, S., Mukherjee, S., 2023. Predicting the magnitude of an impending earthquake using deep learning techniques. Earth Sci. Inf. 16 (1), 803–823. https://doi.org/10.1007/s12145-022-00916-2.

Saffer, D.M., Tobin, H.J., 2011. Hydrogeology and mechanics of subduction zone forearcs: fluid flow and pore pressure. Annu. Rev. Earth Planet Sci. 39 (1), 157–186. https://doi.org/10.1146/annurev-earth-040610-133408.

Saini, K., Kalra, S., Sood, S.K., 2022. An integrated framework for smart earthquake prediction: IoT, fog, and cloud computing. J. Grid Comput. 20 (2), 17. https://doi.org/10.1007/s10723-022-09600-7.

Sarkar, S., Roy, A., Kumar, S., Das, B., 2021. Seismic intensity estimation using multilayer perceptron for onsite earthquake early warning. IEEE Sensor. J. 22 (7), 2553–2563. https://doi.org/10.1109/JSEN.2021.3137395.

Sarwar, B., Bajwa, I.S., Jamil, N., Ramzan, S., Sarwar, N., 2019. An intelligent fire warning application using IoT and an adaptive neuro-fuzzy inference system. Sensors. https://doi.org/10.3390/s19143150.

Scholz, C., 1998. Earthquakes and friction laws. Nature 37–42. https://doi.org/10.1038/34097.

Seoane, V., Garcia-Rubio, C., Almenares, F., Campo, C., 2021. Performance evaluation of CoAP and MQTT with security support for IoT environments. Comput. Network. 197, 108338 https://doi.org/10.1016/j.comnet.2021.108338.

Shah, S., Mahmood, W., 2020. Smart home automation using IoT and its low cost implementation. Int. J. Eng. Manuf. (IJEM) 10 (5), 28–36. https://doi.org/10.5815/ijem.2020.05.03.

Shan, D., Lindsey, N., Wagner, A.M., Daley, T.M., Freifeld, B., Robertson, M., et al., 2017. Distributed acoustic sensing for seismic monitoring of the near surface: a traffic-noise interferometry case study. Sci. Rep. 7 https://doi.org/10.1038/s41598-017-11986-4.

Shinohara, M., Yamada, T., Akuhara, T., Mochizuki, K., Sakai, S., 2022. Performance of seismic observation by distributed acoustic sensing technology using a seafloor cable off Sanriku, Japan. Front. Mar. Sci. 9 https://doi.org/10.3389/fmars.2022.844506.

Song, Z., Rahmadya, B., Sun, R., Takeda, S., 2023. A feasibility study on monitoring earthquake-caused furniture vibrations using radiofrequency identification sensor tags. Sensors 23, 3279. https://doi.org/10.3390/s23063279.

Sreevidya, P., Abhilash, C., Paul, J., Rejithkumar, G., 2021. A machine learning-based early landslide warning system using IoT. In: Proceedings of the 2021 4th Biennial International Conference on Nascent Technologies in Engineering (Icnte), pp. 1–6. https://doi.org/10.1109/ICNTE51185.2021.9487669. Navi Mumbai, India.

Stein, S., Wysession, M., 2003. An Introduction to Seismology, Earthquakes, and Earth Structure. Blackwell Publishing.

Storetvedt, K., 1990. The Tethys sea and the Alpine-Himalayan orogenic belt; mega-elements in a new global tectonic system. Phys. Earth Planet. In. 62 (1), 141–184. https://doi.org/10.1016/0031-9201(90)90198-7.

Su, W, E., W. Z, G., Fan, C., 2016. GPS strain rate and seismic activity before the Ludian earthquake (ms 6.5), northeast Yunnan, China: new implications for eastward chuan-dian block extrusion. Terr. Atmos. Ocean Sci. 27, 837–851. https://doi.org/10.3319/TAO.2016.02.15.01(TT).

Sun, Z., Sandoval, L., Crystal-Ornelas, R., Mousavi, S.M., Wang, J., Lin, C., John, A., 2022. A review of earth artificial intelligence. Comput. Geosci. 105034 https://doi.org/10.1016/j.cageo.2022.105034.

Tehseen, R., Farooq, M.S., Abid, A., 2020a. Earthquake prediction using expert systems: a systematic mapping study. Sustainability 12 (6). https://doi.org/10.3390/su12062420.

Tehseen, R., Farooq, M., Abid, A., 2020b. Fuzzy expert system for earthquake prediction in western Himalayan range. ElektronikairElektrotechnika 26 (3), 4–12. https://doi.org/10.5755/j01.eie.26.3.25744.

Tehseen, R., Farooq, M., Abid, A., 2021. A framework for the prediction of earthquake using federated learning. Peer J. Comput. Sci. 7, e540 https://doi.org/10.7717/peerj-cs.540.

Thompson, J.M.T., Wright, T.J., 2002. Remote monitoring of the earthquake cycle using satellite radar interferometry. Philos. Trans. R. Soc. London, Ser. A: Math. Phys. Eng. Sci. 360 (1801), 2873–2888. https://doi.org/10.1098/rsta.2002.1094.

Tronin, A.A., 2010. Satellite remote sensing in seismology. a review. Rem. Sens. https://doi.org/10.3390/rs2010124.

Turarbek, A., Adetbekov, Y., Bektemesov, M., 2023. 2-d deep convolutional neural network for predicting the intensity of seismic events. Int. J. Adv. Comput. Sci. Appl. 14 (1) https://doi.org/10.14569/IJACSA.2023.0140187.

Uyeda, S., Kanamori, H., 1979. Back-arc opening and the mode of Subduction. J. Geophys. Res. Solid Earth 84 (B3), 1049–1061. https://doi.org/10.1029/JB084iB03p01049.

Vila, M., Sancho, M.-R., Teniente, E., Vilajosana, X., 2023. Critical infrastructure awareness based on IoT context data. Internet of Things 23, 100855. https://doi.org/10.1016/j.iot.2023.100855.

Waldhauser, F., Ellsworth, W.L., 2000. A double-difference earthquake location algorithm: method and application to the Northern Hayward fault, California. Bull. Seismol. Soc. Am. 90 (6), 1353–1368. https://doi.org/10.1785/0120000006.

Wang, D., Abriak, N.E., 2015. Compressibility behavior of dunkirk structured and reconstituted marine soils. Mar. Georesour. Geotechnol. 33 (5), 419–428. https://doi.org/10.1080/1064119X.2014.950798.

Wang, X., Wang, X., Xing, G., Chen, J., Lin, C.-X., Chen, Y., 2012. Intelligent sensor placement for hot server detection in data centers. IEEE Trans. Parallel Distr. Syst. 24 (8), 1577–1588.

Wells, D.L., Coppersmith, K.J., 1994. New empirical relationships among magnitude, rupture length, rupture width, rupture area, and surface displacement, 08 Bull. Seismol. Soc. Am. 84 (4), 974–1002. https://doi.org/10.1785/BSSA0840040974.

Woith, H., 2015. Radon earthquake precursor: a short review. Eur. Phys. J. Spec. Top. 224 (4), 611–627. https://doi.org/10.1140/epjst/e2015-02395-9.

Wortmann, F., Flüchter, K., 2015. Internet of things. Bus. & Inf. Syst. Eng. 57 (3), 221–224. https://doi.org/10.1007/s12599-015-0383-3.

Wu, A., Lee, J., Khan, I., Kwon, Y., 2021. Crowdquake+: data-driven earthquake early warning via IoT and deep learning. In: Proceedings of the 2021 Ieee International Conference on Big Data (Big Data), pp. 2068–2075. https://doi.org/10.1109/BigData52589.2021.9671971. Orlando, FL, USA.

Xie, Y., Ebad Sichani, M., Padgett, J.E., DesRoches, R., 2020. The promise of implementing machine learning in earthquake engineering: a state-of-the-art review. Earthq. Spectra 36 (4), 1769–1801. https://doi.org/10.1177/8755293020919419.
Xin, X., Tu, Y., Stojanovic, V., Wang, H., Shi, K., He, S., Pan, T., 2022. Online reinforcement learning multiplayer non-zero sum games of continuous-time markov jump linear systems. Appl. Math. Comput. 412, 126537 https://doi.org/10.1016/j.amc.2021.126537.
Xiong, P., Tong, L., Zhang, K., Shen, X., Battiston, R., Ouzounov, D., et al., 2021. Towards advancing the earthquake forecasting by machine learning of satellite data. Sci. Total Environ. 771, 145256 https://doi.org/10.1016/j.scitotenv.2021.145256.
Yoshimitsu, O., Kasahara, K., Hori, S., Obara, K., Sekiguchi, S., Fujiwara, H., Yamamoto, A., 2004. Recent progress of seismic observation networks in Japan —Hi-net, F-net, Knet and KIK-net. Earth Planets Space 56. https://doi.org/10.1186/BF03353076 xv–xxviii.
Yousefzadeh, M., Hosseini, S.A., Farnaghi, M., 2021. Spatiotemporally explicit earthquake prediction using deep neural network. Soil Dynam. Earthq. Eng. 144, 106663 https://doi.org/10.1016/j.soildyn.2021.106663.
Zambrano, A.M., Perez, I., Palau, C., Esteve, M., 2017. Technologies of internet of things applied to an earthquake early warning system. Future Generat. Comput. Syst. 75, 206–215. https://doi.org/10.1016/j.future.2016.10.009.
Zebker, H.A., Goldstein, R.M., 1986. Topographic mapping from interferometric synthetic aperture radar observations. J. Geophys. Res. Solid Earth 91 (B5), 4993–4999. https://doi.org/10.1029/JB091iB05p04993.
Zhai, H., Wang, Y., 2022. Design and implementation of earthquake information publishing system based on mobile computing and machine learning technology in GIS. J. Interconnect. Netw. 22, 2145018 https://doi.org/10.1142/S0219265921450183.
Zhao, X., Pan, S., Sun, Z., Guo, H., Zhang, L., Feng, K., 2021. Advances of satellite remote sensing technology in earthquake prediction. Nat. Hazards Rev. 22 (1), 03120001 https://doi.org/10.1061/(ASCE)NH.1527-6996.0000419.
Zhizhin, M.N., Rouland, D., Bonnin, J., Gvishiani, A.D., Burtsev, A., 2006. Rapid estimation of earthquake source parameters from pattern analysis of waveforms recorded at a single three-component broadband station, Port Vila, Vanuatu. Seismological Soc. Am. 96 (6), 2329–2347. https://doi.org/10.1785/0120050172.
Zhou, L., Pan, S., Wang, J., Vasilakos, A.V., 2017. Machine learning on big data: opportunities and challenges. Neurocomputing 237, 350–361. https://doi.org/10.1016/j.neucom.2017.01.026.
Zhou, W., Liang, Y.-w., Ming, Z., Dong, H.-b., 2020. Earthquake prediction model based on danger theory in artificial immunity. Neural Netw. World 30 (4), 231. https://doi.org/10.14311/NNW.2020.30.016.