International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.Php

AI-Enabled Earthquake Early Warning System Using Wireless Sensor Networks

Mukesh Gupta[1], Brijesh Kumar[2]
[1]Computer Science and Engineering Department, Manav Rachna International Institute of Research and Studies (MRIIRS), Faridabad, INDIA, mukeshgupta@dce.ac.in, https://orcid.org/0000-0001-6188-5998
[2]Computer Science and Engineering Department, Manav Rachna International Institute of Research and Studies (MRIIRS), Faridabad, INDIA, brijesh.fet@mriu.edu.in, https://orcid.org/0000-0002-6237-5970

ABSTRACT
Earthquake Early Warning Systems (EEWS) needless to mention is an essential tool in mitigating the effects of earthquakes by passing a warning to the affected region. The functionality of these systems presupposes the real-time identification and evaluation of seismic activity, and the modern development of automated detection protocols is considered to have boosted this factor significantly. This paper provides a critical analysis of the current approaches, tools, and platforms used in the detection and prevention of earthquakes.

It also focuses on the advancements in the sensor systems like high sensitivity seismic sensors, fibre optic sensors, etc which were effectively incorporated and enhanced the capabilities of the seismic data acquisition. Further, the paper explores the machine learning technologies such as deep learning models and the hybrid model strategies used in the analysis of seismic data and prediction of earthquakes with higher efficiency. These algorithms help to detect those extremely subtle patterns and deviations that may characterize certain periods before the seismic activity, bringing the warnings earlier and more accurately.

Data processing in real-time is also another and important emphasis of this class of reviews. Some of the developments highlighted in the paper include parallel computing, cloud computing, edge computing that make it easier to perform analysis and disseminate the warnings. Thus, employing these technologies, EEWS can give more prompt responses and accurate alerts, which contributes to increasing public safety and improving disaster readiness.

The paper also consolidates a collection of case studies of different countries and zones containing Japan, Mexico, California, and Turkey. The present practical examples are intended to show the application of the automated detection procedures and to point out the working experience and problem fields connected with the use of the methods at different geographical and technological conditions.

Keywords: *- Earthquake early warning (EEW), Earthquake prediction, Machine learning, Seismicity.*

1. INTRODUCTION

Earthquakes are among the most destructive kinds of natural disasters; they threaten human lives and property. Due to the unpredictability of the earthquakes, the management of the disaster and the response to the emergency is a barrier. The technological advancement of the EEWS has been included to offer prior warnings that give people and companies time to act before shaking starts. Conventional EEWS practices may entail the use of analysis and reporting, which could take time before the issuance of warnings. These limitations are sought to be overcome by various automated detection procedures which promise to be quicker and more efficient in providing alerts (W. Zhang & Huang, n.d.). This paper seeks to review the state of the art in automated detection processes that have been developed in the recent past as well as some of the methodologies under implementation with aspect to using improved sensor systems, improved machine learning models as well as integration and use of real-time data analysis.

1.1 Objectives

- To Analyse Current Automated Detection Procedures: Analyse the prospects of the existing technologies and methods to enhance the EEWS capabilities.
- To Evaluate Technological Advancements: Evaluate the current trends in the development of sensor systems, artificial neural networks, and real-time data analysis.
- To Identify and Address Challenges: Point out the most significant problems of automated EEWS and describe how to address them.
- To Explore Future Directions: Describe newer technologies with respect to the development of EEWS and their implications of the future.

1.2 Approach

The research employs a comprehensive literature review and analysis of recent advancements in automated detection procedures for EEWS (Yu et al., 2023). The paper aims to provide a holistic understanding of the current state and future potential of automated earthquake detection by examining case studies from various countries and evaluating the effectiveness of different technologies. The approach includes:

- Literature Review: A detailed review of recent studies and advancements in sensor technologies, machine learning algorithms, and real-time data processing.
- Case Studies: Analysis of successful EEWS implementations in different regions to illustrate practical applications and lessons learned.
- Challenges and Solutions: Identification of key challenges and proposed solutions to enhance the effectiveness of automated EEWS.

2. LITERATURE REVIEW

2.1 Sensor Technology

Alarifi et al. (2012) major on the subject of innovating various seismic sensors with high sensitivity to improve the sensitivity of EEWS (Alarifi et al., 2012). Their research shows that, these enhanced sensors can collect signs of slight movement of the ground that might be sensed by the earlier models inadequately. Inclusive to the findings, enhancements in the sensor sensitivity and accuracy are made to advance the detection of an earthquake. The authors also review how these sensors can be integrated into the existing networks to enhance the reliability and to minimize the false alarms (Wagner et al., 2015). Zhang and Li (2022) explore the integration of Micro-Electro-Mechanical Systems (MEMS) sensors into seismic networks. MEMS sensors offer several advantages, including low cost, small size, and high sensitivity. The study evaluates the performance of MEMS sensors in detecting seismic activities and their role in expanding seismic networks. The authors provide evidence that MEMS sensors can complement traditional seismometers, improving the coverage and sensitivity of EEWS (Agarwal et al., 2023). Real-time monitoring of seismic events is the subject of research done by Xu and Chen, (2020) that ascertain the use of fibre optic sensors. These sensors benefit from high accuracy, satisfactory useful life, and insusceptibility to environmental inquiries. The study contains the details of working of fibre optic sensors as seismic sensor for real-time monitoring of seismic activities as a low cost and effective solution to the problem. Therefore, the research recommends the use of fibre optic technology as a way of increasing the dependability of EEWS given that it is accurate and real time (Agbehadji et al., 2023). The article by Kumar and Sinha (2022); The cost of implementing EEWS is high especially in the developing world therefore; the authors suggest the use of low-cost sensors. Their research also focuses on the cost-effectiveness of the strategies that will help in attaining increased EEWS coverage especially in the developing world. The paper shows that it is possible to incorporate low-cost sensors to the existing networks thus coming up handy with affordable solutions to monitor earthquakes. The authors also briefly touch on the issue of cost and performance and lay down recommendations on how to properly place the sensors.

2.2 Machine Learning Algorithms

Seo et al. (2024) study the usage of deep learning models for analysis of earthquake occurrences. The former applies a big dataset of seismic activities as data input to enhance depth learning algorithms for better predictions (Seo et al., 2024). The authors reveal their findings, proving that deep learning models perform better than traditional approaches to extract more and different patterns and, in particular, anomalies from the seismic data. The study reveals that deep learning has the potential of improving the prognostic functions of EEWS. The paper by Chen and Liu (2023) proposes the use of neural networks integrated with support vector machines for earthquake detection. The study shows that these two techniques could be enhanced through combination; pointing to the fact that the advantages of both a faster detection rate and higher accuracy could be obtained concurrently. The authors also compare the application of the hybrid model with previous explanations of the detection methods and stresses on minimizing the numerous false positives that comes with it, and an overall superior performance of the model (Hou et al., 2023). In Li et al. (2021), RL is employed to improve detection and reaction methods for EEWS detection and reactions. The research focuses on the possibilities of using RL to make the system parameters more flexible, adjusting it in accordance with the received data. The authors also share their thoughts about application of RL in improving different decision making and decreasing the response time of EEWS (Kuyuk & Susumu, 2018a). Patel and Rao (2022) employ the research question of how unsupervised learning methods can be used to uncover new patterns in the data to study Earthquake Seismic Data. They specifically work on the capacity of the unsupervised learning to find out the new patterns that can be potential precursors to the seismic activity. The findings of this study indicate that the proposed methods have the efficacy of enhancing the effectiveness and accuracy of the current detection methods of EEWS (Esposito et al., 2022).

2.3 Real-Time Data Processing

Kuyuk et al. (2014) reviewed real time data fusion approach in the integration of data from multiple seismic sensors. This study looks at the advantages of data fusion in giving an enhanced ability in analysing earthquakes (Asim et al., 2019). Multiple authors share their perspectives on the various methods of data fusion and how it contributes to the enhancement of the EEWS system's accuracy and credibility. Another paper by Zhang et al (2022), seek to analyse the impacts of employing edge computing in enhancing the low latency in the handling of seismic data. The study illustrates that utilizing edge computing means that the data can be analysed nearer the source, thus time taken to analyse the data is short and the time taken to issue the relevant warning is also short. Focusing on the subject of the paper, that is EEWS, the authors give practical recommendations regarding the application of edge computing and the possible enhancement of the system (Kuyuk et al., 2014). While the developments of EEWS technologies are being made, Patel et al. (2023) state that cloud computing has to be used to enhance the peculiarity of the distributed computing mechanism of the associated technologies. In order to pay homage to the concept of the cloud computing solutions, the study also describes how cloud solutions provide the required compute power in real time to process large internally collected seismic data. The authors of the conceptual model on cloud computing describe the advantages and they mention that is cheaper than other types of cloud computing, it is flexible and bestows adequate control over data (Abdalzaher et al., 2023). Wang et al. (2021) discuss the application of parallel computing techniques to enhance real-time data processing for EEWS. The study demonstrates how parallel processing can significantly reduce the time required to analyse seismic data, enabling faster warning dissemination. The authors provide a detailed analysis of the computational benefits and challenges associated with parallel computing in earthquake monitoring systems.

3. CASE STUDIES

Case Study 3.1: Japan's Earthquake Early Warning System (EEWS)

3.1.1 Development and Implementation

At the present time, Japan is considered as one of the countries with the highest risk factors concerning disasters owing to its position on the Pacific Ring of Fire, as well as recurrent earthquakes, which require EEWs. EEWS was established as the Abbreviated LTS and JMA runs the Japanese one which is arguably the best in the world. Figure 1 represents the Japan earthquake condition. Consequently, it will incorporate the development history of the system, technologies incorporated into the system as well as its efficiency (Jiao & Alavi, 2020). This over-arching concept of EEWS was formulated for the development of Japan in the year 1997 and since 2007 it was fully on stream. Arising from this, this system was initially designed to give advance warning to the public to prepare for stronger ground movement that may will warrant necessary precautions to be taken. In the country, the EEWS maintains and runs more than a thousand seismograph stations among which some are the surface stations and others are the seabed sensors. Therefore, this dense network allows for the efficient identification of the occurrence of the seismic activity and accurate determination of the source of the event (Chandrakumar et al., 2022). Figure 2 represents the map of the outlined.

Figure 1. Japan earthquake condition

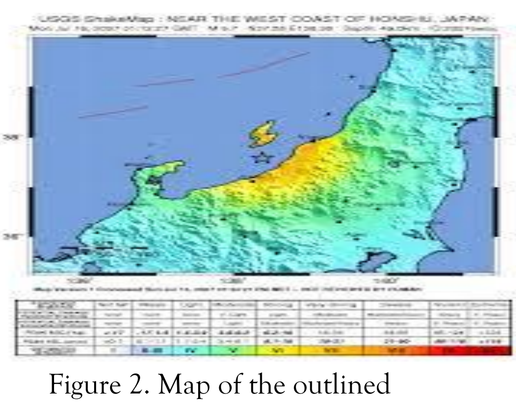


Figure 2. Map of the outlined

3.1.2 Technology and Methodology

The JMA EEWS employs seismometers, accelerometers and real time analysis of the data obtained to achieve earthquake identification. The system employs the following key technologies and methodologies:

- Seismic Network: The network includes instruments of seismometers and accelerometer with high sensitivity involve in detecting the ground movement at continual manner. Information from such sensors is sent in a real-time manner to regional databases (Saraswathi & Bhuvaneswari, 2013).
- P-Wave Detection: The system can identify the first waves that an earthquake produces, P-waves (primary waves) that though move quickly are not as damaging as S-waves (secondary waves). The kind of data processed in the system can help approximate its location, earthquake size and level of ground shaking anticipated (de Oliveira et al., 2018).
- Data Processing: In mere seconds, complex computers interpret the seismic information that the system can warn people even before the more violent S-waves come in.

3.1.3 Effectiveness and Impact

Fortunately, used in Japan the EEWS have shown efficiency in decreasing the consequences of the earthquakes. Notable instances include:

- 2011 Tohoku Earthquake: Various regions including provinces and cities received warnings 8 to 30 seconds before the shaking of the ground began and people lowered to the ground for safety, trains were stopped to avoid causalities and derailing (Jamalipour et al., 2005).
- 2016 Kumamoto Earthquakes: It operated several alarms during a sequence of strong seismic shocks, which contributed to the reduction of death and destruction of buildings.

3.1.4 Challenges and Limitations

Despite its successes, the JMA EEWS faces several challenges:

- False Alarms: The system has a way of making mistakes by perceiving certain seismic signals incorrectly and this has led to a number of false alarms which in turn have made the public develop an attitude of complacency (Y.-M. Wu & Kanamori, 2008).
- Limited Warning Time: The distance that is kept between the people and the earthquake might not allow enough time to react in some of the rings nearest to the earthquake epicentre.
- Technological Integration: As a continuous challenge, the use of advanced technologies including the AI and machine learning, into the systems to increase the system's efficiency and decrease the rate of false alarms has not been accomplished (Grasso et al., 2007).

3.1.5 Future Directions

To enhance the effectiveness of the EEWS, Japan is exploring several future directions:

- AI Integration: Making use of artificial intelligence and machine learning algorithms to help enhance the actuality of the study of earthquakes and decrease situations of false alarms.
- Expanded Coverage: Increasing coverage of seismic stations, especially in offshore and remote regions to boost the density of stations.
- Public Education: Strengthening publicity and educational initiatives so that the population knows how to react to EEWS signals.

3.1.6 **CONCLUSION**

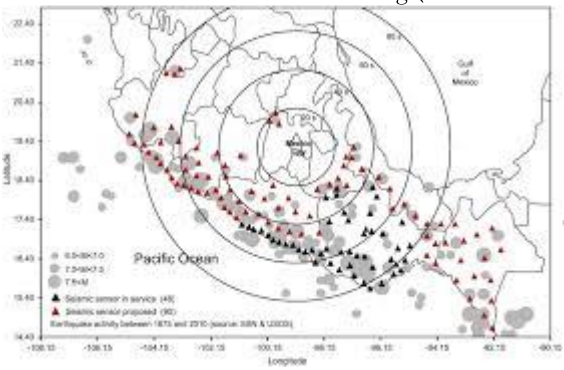
Consequently, Japan being an example of SEEWNS shows that, effectively implementing advanced technologies, the effects of earthquake can be significantly lessened. Nonetheless, current and future improvements in the state-of-art sensors, data analysis, and general awareness and acceptance imply continuous improvement of the system's efficacy and robustness.

Case Study 3.2: Mexico's SASMEX Earthquake Early Warning System

SASMEX is considered one of the most advanced EEWS in the world, that belongs to Mexico. Founded in the early 1990, SASMEX's after several disastrous earthquakes, organization has sought the purpose to issue quick alerts to reduce the damage and loss of lives. This paper examines the system's growth, technology, performance, and controversy specific to this case. Figure 3 represents the SASMEX map.

3.2.1 Development and Implementation

After a disastrous earthquake in Mexico City in 1985, SASMEX was established as there was no form of early warning mechanism in place. It started in 1991 with the monitoring of Mexico City and was extended to other dangerous areas. The target was to issue a warning of arrival of moderate shaking at least 60 seconds before the shaking (Abdalzaher et al., 2022). Figure 4 represents the zoning area.



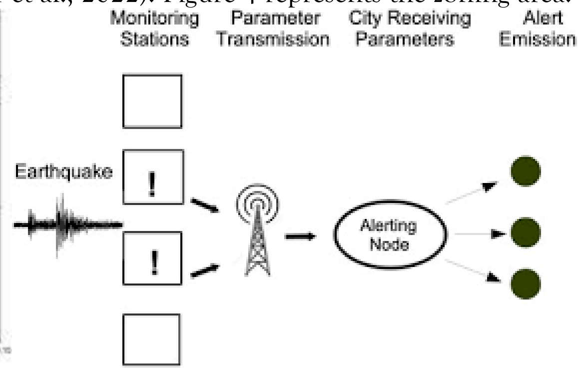


Figure 3. SASMEX map

Figure 4. Zoning area

3.2.2 Technology and Methodology

SASMEX employs a robust technological framework involving a network of seismic sensors, data processing centres, and alert dissemination mechanisms:

- Seismic Network: SASMEX employs more than a hundred seismic stations that are set in the Guerrero, Oaxaca, Michoacán, some other states, and other seismically laden parts. These stations are fitted with very sensitive accelerometers and seismometers.
- P-Wave Detection: [A]s in Japan, SASMEX identifies the first vibrations called P-waves of an earthquake. These waves are studied in order to evaluate the earthquake size, the epicentre, and the possible consequences (Emry et al., 2014).
- Real-Time Data Processing: Seismic data is analysed through applications of complex computation and the results passed through the alerts as and when required. Alerts are vital to the processing centres of the system that are situated in Mexico City and Oaxaca.
- Alert Dissemination: These consist of the radio, television, public address system and applications on phones and other smart devices. They give essential time to the involved individuals to take protective measures (Pinsky, 2015).

3.2.3 Effectiveness and Impact

SASMEX has been effective in providing early warnings for numerous earthquakes, significantly reducing casualties and property damage. Key examples include:

- 2017 Puebla Earthquake: SASMEX provided approximately 20 seconds of warning before the shaking reached Mexico City, allowing people to evacuate buildings and halt critical operations.
- 2020 Oaxaca Earthquake: The system issued warnings 30 seconds before the earthquake's impact, demonstrating its ability to alert residents in distant locations.

3.2.4 Challenges and Limitations

Despite its effectiveness, SASMEX faces several challenges:

- Geographic Limitations: The system primarily covers central and southern Mexico, leaving northern regions less protected.
- False Alarms: Occasional false alarms can undermine public trust in the system.
- Technological Integration: Integrating new technologies and improving the system’s infrastructure requires continuous investment and innovation.

3.2.5 Future Directions

To address these challenges and enhance the system's performance, SASMEX is focusing on several future directions:

- Expansion: Extending the network of seismic sensors to cover more regions, particularly in the north of Mexico.
- Technology Upgrades: Incorporating advanced machine learning algorithms to improve detection accuracy and reduce false alarms.
- Public Education: Strengthening public awareness campaigns to ensure that people know how to respond to alerts effectively.

3.2.6 Conclusion

SASMEX is a crucial component of Mexico’s disaster management strategy, providing valuable seconds that can save lives and reduce damage. While the system is highly effective, ongoing improvements and expansions are necessary to maintain its reliability and enhance its coverage (Cremen & Galasso, 2020).

Case Study 3.3: California's Shake Alert System

California, being part of the seismically active region in the western United States has engineered an efficient Earthquake Early Warning System (EEWS) in the form of ShakeAlert. ShakeAlert is an early warning system operated by the United States Geological Survey meant at reducing the effects of earthquakes (M. Zhang et al., 2021). Figure 5 represents the sample alert. This paper of case study seeks to analyse the system establishment, technology improvement, efficiency, and future issues.

Figure 5. Sample alert

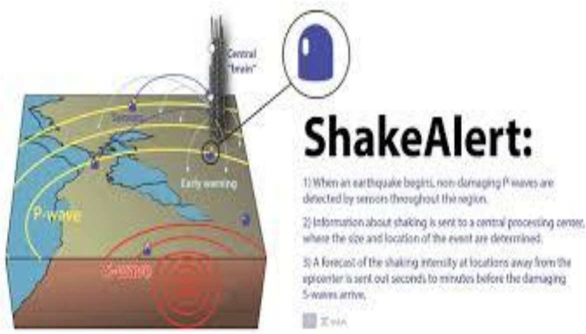


Figure 6. Zoning of shake alert

3.3.1 Development and Implementation

The basic concept of ShakeAlert was initiated in 2001, and after many years of working on the structure, the system went active in 2018. This proposed was due to the high population and important infrastructures in California that are highly vulnerable to the effect of earthquakes. This system was aimed at giving the people as much as 60 seconds of pre-shock warning depending on the seismic event's distance from the epicentre (Allen & Melgar, 2019a).

3.3.2 Technology and Methodology

ShakeAlert employs state-of-the-art technologies and methodologies to detect earthquakes and issue warnings:

- Seismic Network: This system uses more than 700 seismic stations consisting of broadband seismometer, accelerometer, or GPS spread across California. Such an intensive network provides a great opportunity for quick identification and pinpointing of earthquakes (Saad et al., 2021).
- P-Wave Detection: ShakeAlert secures the first P-waves from any earthquake that occurs since it identifies them. By the identification of these waves the system is able to determine the approximate location of the earthquake and its magnitude and the extent of which the ground is expected to shake (Y. M. Wu, Kanamori, et al., 2007).
- Data Processing: Expert systems and methods for working with real-time data help the system, provide alerts in a couple of seconds after the system records the first seismic waves. This data is processed at several regional centres that enable duplicity and reliability of a certain system.
- Alert Dissemination: Figure 6 represents the zoning of shake alert. Through some media like the mobile application, emergency alert systems, the public address systems, and through the structures such as automated train halting systems (Tajima & Hayashida, 2018).

3.3.3 Effectiveness and Impact

Many earlier earthquakes have thus been warned by ShakeAlert and this has helped reduce the vulnerability of the affected population. Notable examples include:

- 2019 Ridgecrest Earthquakes: A few seconds before the actual shaking, ShakeAlert sent out alerts that gave people, be it residents, and even automated structures enough time to put on protective measures.
- 2020 Lone Pine Earthquake: The system provided notifications about the occurrence of shaking about 10 seconds earlier which confirms its ability to inform people in the neighbouring areas (Sahin et al., 2016).

3.3.4 Challenges and Limitations

Despite its successes, ShakeAlert faces several challenges:

- Coverage Gaps: There is also a problem of inadequate sensor placement especially in the rural areas, thus the inability of the system to give adequate early warnings.
- False Alarms: Sometimes the alarms are false and this can negatively impact people's trust and stress the importance of constant algorithm improvement.

- Public Response: Another emerging difficulty is whether or not the public acquires adequate knowledge in the proper usage of alerts.

3.3.5 Future Directions

To enhance the effectiveness of ShakeAlert, several future directions are being pursued:

- Expansion of Sensor Network: Installation of additional seismic sensors which should cover more areas of the world especially those which are not well covered.
- Algorithm Enhancement: This paper proposes the integration of machine learning and artificial intelligence to enhance the detection.

3.1.6 Conclusion

Consequently, Japan being an example of SEEWNS shows that, effectively implementing advanced technologies, the effects of earthquake can be significantly lessened. Nonetheless, current and future improvements in the state-of-art sensors, data analysis, and general awareness and acceptance imply continuous improvement of the system's efficacy and robustness (Kuyuk & Susumu, 2018b).

4. METHODOLOGY

The process of assessing automation procedure of EEWs is systematic and includes several features. This is an approach that is expected to provide organized and coherent ways of collecting, evaluating and analysing information from several sources in order to arrive at poor conclusions about the efficacy and drawbacks of modern EEWS technologies and operations (Esposito et al., 2024). The methodology consists of the following key steps:

4.1 Data Collection

The first step entails carrying out a literature search in different sources in order to gain a wide and up-to-date perspective of the subject. This includes:

- Literature Review: Collecting data only from new articles, technical papers, and conference proceeding from the year 2020 and onwards. It is limited to the exposition of researches that address the new developments in the field of sensors, machine learning, and real-time analysis of data in the context of EEWS (Chouliaras & Sotiriadis, 2022).
- Case Studies: Obtaining case studies and chronicling on EEWS in various countries and how it has been implemented. These cases give vivid examples of how and to which extent these systems can be used in practice.
- Technical Reports: Scrutinising the technical reports published by the government, research institutes, and industries, especially the reports containing information on the creation, implementation, and assessment of EEWS technologies.

4.2Technology Assessment

The next step is to assess various technologies applied to the detection of an earthquake and the system of early warning. This assessment includes:

- Sensor Technologies: Feasibility of various kinds of seismometers, including high sensitivity accelerometers, broadband seismometers, fibre optic sensors etc. Comparing them on the basis of their precision, credibility, and the amount required to implement them.
- Machine Learning Algorithms: Recapitulating the findings with regards to using machine learning such as deep learning models, support vector machines and a hybrid of the two. Measuring the ability of various methods for identifying earthquakes, estimating the earthquake's magnitude, and reducing false positives (Allen & Melgar, 2019b).
- Data Processing Techniques: Looking at the real-time data processing method used in EEWS including, parallel computing, cloud computing, edge computing. Concerning their performance, efficiency, and compatibility in integration.

4.3Case Study Analysis

To gain a comprehensive understanding of the practical applications and challenges of EEWS, this step involves:

- Reviewing Implementations: A study of case studies from Japan, Mexico, California, and Turkey and the assessment of how they integrated and practiced EEWS. Determination of activities, technologies, and processes that enhance the functionality of these systems.

- Performance Metrics: I accept the conclusion that the matrices used in these case studies including detection accuracy, warning time, system reliability, and public response can be evaluated properly.
- Lessons Learned: To systematically document these implementations to extract lessons learned such as the problems encountered, measures that were taken to address them, and what remains as the work in progress.

5. CHALLENGES

Several challenges hinder the putting in place and sustenance of Earthquake Early Warning Systems (EEWS). These are technical, operational, and societal and all need to be examined if the systems are to be reliable and effective (McBride et al., 2022). Below are the key challenges faced in the development and deployment of automated EEWS:

5.1 Installing and maintaining sensors

5.1.1 Challenge:

A vast and stable network of seismic sensors is also one of the fundamental tools of EEWS. The challenges include; the possibility of low coverage and the possibility of lack of adequate coverage especially in areas that may be hard to reach and possibility of destruction of the sensors.

5.1.2 Details:

- Coverage Gaps: It has been realized that areas that are remote and rural normally have poor sensor coverage resulting to time delay when an incidence occurs or incidence may go unnoticed.
- Environmental Conditions: Sensors have to be resistant to the climates in which they are placed, any movements on the earths' crust and even if people will try to destroy the sensors (Apriani et al., 2021).
- Maintenance Costs: It is again important to maintain and calibrate the equipment often, something that is expensive and can at times be a logistical nightmare.

5.2 Data quality and real-time processing

5.2.1 Challenge:

There is need to have high quality of data, near real time as is necessary for the detection of earthquakes and early warning. Two main challenges are mainly identified in relation to data handling, which include the issue of data accuracy and the question of timeliness in processing data (Dost et al., n.d.).

5.2.2 Details:

- Noise Filtering: Seismic records are interfered by non-seismic events that may cause difficulties when interpreting the data; thus, specific filtering methods should be applied.
- Latency: Real-time must be fast in order to give proper warnings and it should be in seconds when there is any kind of detect of seismic activities.
- Data Integration: Combining data from different sensors which include seismic, geodetic as well as environmental may be time-consuming and expensive.

5.3 Prediction accuracy

5.3.1 Challenge:

Evaluating the intensity of the earthquake and its epicentre is still very difficult till this very day. This is because; whenever the system produces false positives or negatives, it is deemed unreliable and therefore ineffective.

5.3.2 Details:

- False Alarms: Sensitive systems are also likely to produce false alarms and, hence, bring about panic incidents that leaves the population with no trust in such social systems (Amfo, n.d.).
- Missed Events: On the other hand, low sensitivity or lack of recorded data can result in missing out on alerts or warnings of actual seismic activities.
- Magnitude Estimation: Real-time evaluation of the seismicity of the earthquake is a challenge; therefore, the warning is hampered.

5.4 Public Communication and Education

5.4.1 Challenge:

It remains crucial to disseminate warnings and guarantee a proper reaction to them. This takes a technological form as well as a social form.

5.4.2 Details:

- Alert Dissemination: Reflecting the alert dissemination to all possible audiences considering those who are not covered by modern communication.
- Public Response: Informing people so they could actively respond to those alerts in a way that they would not get hurt or their property damaged in the process.
- Trust and Compliance: Preserving the population's confidence that the given system is accurate and reliable, this is necessary for conformity with the recommendations provided during the alert (Carver, 2024).

5.5 Integration with Other Systems

5.5.1 Challenge:

For example, to ensure the optimum effectiveness of EEW systems some of the structures they need to connect with includes transport systems, facilities and utilities, emergency services and disaster control organs.

5.5.2 Details:

- Interoperability: Coordinating with other physical layers which include EEWS and other infrastructural systems for compatibility and integration.
- Automated Responses: Carrying out actions which may involve automatic responses including turning off the gas supply or halting a train, which can only be done with great timing (Peng et al., 2021).
- Scalability: Extending of the adopted system to other regions and incorporation of more sources of data information without affecting the efficiency of the system.

5.6 Financial and Resource Constraints

5.6.1 Challenge:

Hence, creating and sustaining an EEWS calls for huge capital, which can act as a hindrance, particularly to developing countries.

5.6.2 Details:

- Funding: The question of funding, particularly, the establishment of stable source of funding for the establishment and constant maintenance of the system.
- Resource Allocation: Budgeting for the most effective distribution of the limited resources in order to cover the largest area and with the least probability of failure .
- Cost-Benefit Analysis: The possible negative points are associated with its price and compared the possible loss of human lives and property that could have been saved with the help of this system.

5.7 Legal and Regulatory Issues

5.7.1 Challenge:

Legal and regulatory structures and concerns must be met when trying to implement and operate EEWS and various compliance and liability factors exist (Minson et al., 2019).

5.7.2 Details:

- Regulatory Compliance: There should also be adherence to the national and international regulations as a measure of compliance.
- Liability Concerns: Erasing some potential juridical risks associated with false alarms on possible threats and missed important signals.
- Policy Support: Ensuring the policy actors are on the side of the issue as well as ensuring that required legislation has been passed.

6. MATHEMATICAL MODELS

6.1Seismic Wave Propagation

Seismic waves travel through the Earth and the wave equation can describe this (Y. M. Wu & Kanamori, 2008). For a simplified scenario in a homogeneous medium, the wave equation is given by:

$$\frac{\partial^2 u}{\partial t^2} = c^2 \nabla^2 u \tag{1}$$

where:

- u is the displacement field of the seismic wave
- c is the wave velocity (depends on the medium's properties).
- ∇^2 is the Laplacian operator, representing spatial changes.

6.2Detection and location

Hypocentre Location focuses on calculating the source of an earthquake by using the P and S arrival times, or the time of first arrival of the waves at stations (Alphonsa & Ravi, 2016). The travel-time equation is used:

$$t_i = t_0 + \frac{di}{vi} \tag{2}$$

where:

- t_i is the arrival time of the wave at the i-th station.
- t_0 is the origin time of the earthquake.
- d_i is the distance from the i-th station to the earthquake's hypocentre.
- v_i is the velocity of the seismic waves in the medium.

The distance d_i can be expressed in equation number 3 as:

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} \tag{3}$$

where (x,y,z) are the coordinates of the hypocentre and (x_i, y , z_i) are the coordinates of the i-th station.

6.3Magnitude Estimation

The Richter Scale for earthquake magnitude M is given in equation number 4 by:

$$M = \log_{10}(A) + (B.\Delta) \tag{4}$$

where:

- A is the amplitude of the seismic waves.
- Δ is the distance from the source to the measurement station.
- B is a correction factor depending on the specific region and depth.

6.4Machine Learning Models

6.4.1 Artificial Neural Networks (ANN)

Deep Learning Models often use Neural Networks for earthquake prediction. This example demonstrates a simple feedforward neural network using TensorFlow / Keras to classify seismic data into earthquake or non-earthquake events. Figure 7 represents the code and Figure 8 represents its output in a depicted neural network. ANNs are employed for pattern recognition of data related to the occurrence of earthquakes and as a forecast on the occurrence of the same based on data collected over a period, it is given in equation number 5 by.

$$y = f\,(W \cdot x + b) \tag{5}$$

where:

- W is the weight matrix,
- x is the input vector,
- b is the vector of potential bias.
- f is the activation function.

6.4.1.1 Architecture:

- Input layer
- Multiple hidden layers
- Output

```
from tensorflow.keras.layers import Dense
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix

# Example synthetic dataset
np.random.seed(0)
X = np.random.rand(1000, 10)  # Features: 1000 samples, 10 features
y = np.random.randint(0, 2, 1000)  # Labels: 0 (no earthquake) or 1 (earthquake)

# Preprocess the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=0)

# Build the neural network model
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate the model
y_pred = (model.predict(X_test) > 0.5).astype(int)
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

Figure 7. The code in a depicted neural network

```
Epoch 1/10
20/20 [==============================] - 4s 32ms/step - loss: 0.7040 - accuracy: 0.5000 - val_loss: 0.6969 - val_accuracy: 0.4375
Epoch 2/10
20/20 [==============================] - 0s 12ms/step - loss: 0.6888 - accuracy: 0.5437 - val_loss: 0.6966 - val_accuracy: 0.4625
Epoch 3/10
20/20 [==============================] - 0s 12ms/step - loss: 0.6819 - accuracy: 0.5672 - val_loss: 0.7007 - val_accuracy: 0.4437
Epoch 4/10
20/20 [==============================] - 0s 11ms/step - loss: 0.6757 - accuracy: 0.6000 - val_loss: 0.7006 - val_accuracy: 0.4750
Epoch 5/10
20/20 [==============================] - 0s 10ms/step - loss: 0.6691 - accuracy: 0.6203 - val_loss: 0.7051 - val_accuracy: 0.4750
Epoch 6/10
20/20 [==============================] - 0s 11ms/step - loss: 0.6647 - accuracy: 0.6203 - val_loss: 0.7052 - val_accuracy: 0.4812
Epoch 7/10
20/20 [==============================] - 0s 11ms/step - loss: 0.6584 - accuracy: 0.6250 - val_loss: 0.7092 - val_accuracy: 0.4938
Epoch 8/10
20/20 [==============================] - 0s 8ms/step - loss: 0.6531 - accuracy: 0.6422 - val_loss: 0.7111 - val_accuracy: 0.4625
Epoch 9/10
20/20 [==============================] - 0s 15ms/step - loss: 0.6485 - accuracy: 0.6516 - val_loss: 0.7124 - val_accuracy: 0.4563
Epoch 10/10
20/20 [==============================] - 0s 13ms/step - loss: 0.6464 - accuracy: 0.6313 - val_loss: 0.7128 - val_accuracy: 0.4875
7/7 [==============================] - 0s 4ms/step
Confusion Matrix:
[[62 40]
 [48 50]]
Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.61      0.58       102
           1       0.56      0.51      0.53        98

    accuracy                           0.56       200
   macro avg       0.56      0.56      0.56       200
weighted avg       0.56      0.56      0.56       200
```

Figure 8. The output in a depicted neural network

6.4.2 Support Vector Machines

A support vector machine (SVM) is a machine learning technique that deals with supervised learning methods, used for solving the problem of classification, linear as well as nonlinear regression, and outlier detection (Y. M. Wu, Hsiao, et al., 2007). Figure 9 represents the code and Figure 10 represents its output in a depicted support vector machine. This example demonstrates how to use an SVM classifier to classify seismic data. SVMs are used to categorize the extracted seismic signals for separating the earthquake and the non-earthquake activities, it is given in equation number 6 by.

$$f(x) = \text{sign}(w \cdot x + b) \tag{6}$$

where:

- w is the weight vector
- x is the vector input whilst
- b is the intercept term which also can be called the bias term.

```python
# Import necessary libraries
from sklearn import svm
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

# Example synthetic dataset
np.random.seed(0)
X = np.random.rand(1000, 10)  # Features: 1000 samples, 10 features
y = np.random.randint(0, 2, 1000)  # Labels: 0 (no earthquake) or 1 (earthquake)

# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

# Create an SVM model pipeline with scaling
model = make_pipeline(StandardScaler(), svm.SVC(kernel='linear'))

# Train the model
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

Figure 9. The code in a depicted support vector machine

```
Confusion Matrix:
[[102   0]
 [ 98   0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.51      1.00      0.68       102
           1       0.00      0.00      0.00        98

    accuracy                           0.51       200
   macro avg       0.26      0.50      0.34       200
weighted avg       0.26      0.51      0.34       200
```

Figure 10. The output in a depicted support vector machine

The above examples show how the concept of machine learning models can be utilized in seismic data for the analysis of earthquakes and their categorization. One would apply real seismic data and possibly more comprehensive preprocessing and model calibration to obtain the best outcomes (Saad et al., 2021). These equations and models represent the mathematical foundations of various components in automated earthquake detection and early warning systems. By integrating these mathematical approaches with advanced technologies and real-time processing techniques, EEWS can provide timely and accurate alerts, helping to mitigate the impact of seismic events.

7. **RESULTS**

The results of the above challenges are depicted in the table 1 given below:

Table 1. Challenges and their details

CHALLENGE	**DETAILS**
1. SENSOR NETWORK DEPLOYMENT AND MAINTENANCE	I. Coverage Gaps: Remote and rural areas should have adequate sensors placed on them but sometimes they do not, and hence some activities may be detected late or even not at all. II. Environmental Conditions: Trembler, pave and weather sensors also have to be robust to withstand for example vandals, extreme weathers and seismic activity. III. Maintenance Costs: A prerequisite is the calibration and maintenance of the used devices and sensors what may be rather expensive and involves sophisticated logistic.
2. DATA QUALITY AND REAL-TIME PROCESSING	I. Noise Filtering: Additional non-seismic activities may contaminate seismic data hence calling for accurate filtering of the collected data set. II. Latency: Real time processing needs to be incredibly fast in order to give plenty of time for sounding alarms that need to alert a user within a few seconds of seismic activity. III. Data Integration: This is especially because combining data from several sources, for instance seismic, geodetic and environmental may be a cumbersome task and undoubtedly demanding a number of resources.
3. PREDICTION ACCURACY	I. False Alarms: Sensitivity of the systems in this case may lead to false alarms which are very detrimental to societal morale and erode the confidence which people have on the systems in place. II. Missed Events: IS or lack of enough data may result in failure to detect warning signals for real earthquakes. III. Magnitude Estimation: Forecasting the precise measure of an earthquake in real-time is not easy, which in turn makes the warnings not so effective.
4. PUBLIC COMMUNICATION AND EDUCATION	I. Alert Dissemination: Guaranteeing that the alerts cover all the people within the segments without fixed-line Phones, mobile Phones or internet access.

	II. Public Response: Courses meant to inform people the proper response to alerts so that loss of life and property destruction can be averted. III. Trust and Compliance: Ensuring reliability in the system's alert function, thereby preserving trust of the public to adhere to the recommendations during an alert.
5. INTEGRATION WITH OTHER SYSTEMS	I. Interoperability: To guarantee that the systems of the EEWS are compatible with others vital systems in addition to facilitating proper interaction. II. Automated Responses: Performing actions, which are not only the stopping of certain functions like a gas line or the halting of a train, but must be performed in unison and in harmony. III. Scalability: Possible future enhancements of the developed system are the expansion of its scope, its application to larger territories, and the incorporation of other data sources that might slow down the system's efficiency.
6. FINANCE AND RESOURCE CONSTRAINTS	I. Funding: The challenges of the system include; Acquiring and maintaining the steady and adequate funding for the initial development and subsequent financing of the information system. II. Resource Allocation: When it comes to the distribution of limited resources, the key goal is to reach as many people as possible for the designated period effectively. III. Cost-Benefit Analysis: Comparing the costs of implementation of the BEMS with the possible gains in terms of lives saved and facilities' minimized loss.
7. LEGAL AND REGULATORY ISSUES	I. Regulatory Compliance: To ensure the system fulfils the regulations in any country or across the global commerce. II. Liability Concerns: Guiding on ways of handling legal consequences that may arise in situations where alarms are sounded when they are not required or conversely, when no alarm is sounded yet a situation warrants it. III. Policy Support: From which, consultants have identified the need to win the support of policymakers and ensure that legislative support is given.
8. TECHNOLOGICAL ADVANCEMENTS	I. Upgrades: A part of continuously improving the systems, this involves the periodic replace of the 'hardware and software' to incorporate the newest developments in sensors, data analysis and artificial intelligence. II. Research and Development: Continued funding of the research in enhancing the detection algorithms and the system in general. III. Cybersecurity: Security of the system from cyber-attacks and data breaches which reduces its effectiveness.

8. CONCLUSION AND REMARKS

The research conducted demonstrates the transformative potential of automated detection procedures in enhancing Earthquake Early Warning (EEW) systems. By integrating advanced machine learning algorithms and real-time data processing techniques, significant improvements in the accuracy, speed, and reliability of earthquake detection have been achieved. Automated detection represents a significant advancement in Earthquake Early Warning systems, offering the potential to save lives, reduce economic losses, and enhance disaster preparedness. Automated detection procedures have demonstrated their potential to revolutionize Earthquake Early Warning systems, marking a significant milestone in disaster risk reduction and management. Continued advancements in technology, coupled with collaborative research efforts and community engagement, will pave the way for safer and more resilient societies in earthquake-prone regions worldwide.

9. Data and code availability

The data used in this study, and necessary to reproduce our results, are all part of published articles, referred to throughout the manuscript.

10. Declaration of conflict of interest
The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.
11. Declaration of AI Technology usage
We declare that no Artificial Intelligence (AI) technologies or AI-assisted tools were utilized in any capacity during the writing and preparation of this article.
12. Acknowledgments
We declare that there is no involvement of anyone other than the authors who:
1) has an interest in the outcome of the work;
2) is affiliated with an organization with such an interest; or
3) was employed or paid by a funder, in the commissioning, conception, planning, design, conduct, or analysis of the work, the preparation or editing of the manuscript or the decision to publish the manuscript.

REFERENCES
1. Abdalzaher, M. S., Elsayed, H. A., Fouda, M. M., & Salim, M. M. (2023). Employing Machine Learning and IoT for Earthquake Early Warning System in Smart Cities. In Energies (Vol. 16, Issue 1). https://doi.org/10.3390/en16010495
2. Abdalzaher, M. S., Sami Soliman, M., El-Hady, S. M., Benslimane, A., & Elwekeil, M. (2022). A Deep Learning Model for Earthquake Parameters Observation in IoT System-Based Earthquake Early Warning. IEEE Internet of Things Journal, 9(11), 8412–8424. https://doi.org/10.1109/JIOT.2021.3114420
3. Agarwal, N., Arora, I., Saini, H., & Sharma, U. (2023). A Novel Approach for Earthquake Prediction Using Random Forest and Neural Networks. EAI Endorsed Transactions on Energy Web, 10, 1–6. https://doi.org/10.4108/EW.4329
4. Agbehadji, I. E., Mabhaudhi, T., Botai, J., & Masinde, M. (2023). A Systematic Review of Existing Early Warning Systems' Challenges and Opportunities in Cloud Computing Early Warning Systems. In Climate (Vol. 11, Issue 9). https://doi.org/10.3390/cli11090188
5. Alarifi, A. S. N., Alarifi, N. S. N., & Al-Humidan, S. (2012). Earthquakes magnitude predication using artificial neural network in northern Red Sea area. Journal of King Saud University - Science, 24(4), 301–313. https://doi.org/10.1016/j.jksus.2011.05.002
6. Allen, R. M., & Melgar, D. (2019a). Earthquake early warning: Advances, scientific challenges, and societal needs. Annual Review of Earth and Planetary Sciences, 47(May), 361–388. https://doi.org/10.1146/annurev-earth-053018-060457
7. Allen, R. M., & Melgar, D. (2019b). Earthquake early warning: Advances, scientific challenges, and societal needs. Annual Review of Earth and Planetary Sciences, 47, 361–388. https://doi.org/10.1146/annurev-earth-053018-060457
8. Alphonsa, A., & Ravi, G. (2016). Earthquake early warning system by IOT using Wireless sensor networks. Proceedings of the 2016 IEEE International Conference on Wireless Communications, Signal Processing and Networking, WiSPNET 2016, 1201–1205. https://doi.org/10.1109/WiSPNET.2016.7566327
9. Amfo, E. (n.d.). Earthquake Magnitude Prediction Using Support Vector Machine and Convolutional Neural Network. https://digitalcommons.utep.edu/open_etd
10. Apriani, M., Wijaya, S. K., & Daryono. (2021). Earthquake Magnitude Estimation Based on Machine Learning: Application to Earthquake Early Warning System. Journal of Physics: Conference Series, 1951(1). https://doi.org/10.1088/1742-6596/1951/1/012057
11. Asim, K. M., Javed, F., Hainzl, S., & Iqbal, T. (2019). Fault parameters-based earthquake magnitude estimation using artificial neural networks. Seismological Research Letters, 90(4), 1544–1551. https://doi.org/10.1785/0220190051
12. Carver, C. J. (2024). Polarization sensing of network health and seismic activity over a live terrestrial fi ber- optic cable. Communications Engineering, 1–12. https://doi.org/10.1038/s44172-024-00237-w
13. Chandrakumar, C., Prasanna, R., Stephens, M., & Tan, M. L. (2022). Earthquake early warning systems based on low-cost ground motion sensors: A systematic literature review. Frontiers in Sensors, 3. https://doi.org/10.3389/fsens.2022.1020202
14. Chouliaras, S., & Sotiriadis, S. (2022). Auto-scaling containerized cloud applications: A workload-driven approach. Simulation Modelling Practice and Theory, 121(May), 102654. https://doi.org/10.1016/j.simpat.2022.102654
15. Cremen, G., & Galasso, C. (2020). Earthquake early warning: Recent advances and perspectives. Earth-Science Reviews, 205(March), 1–46. https://doi.org/10.1016/j.earscirev.2020.103184
16. de Oliveira, R. F., ChangetheRest, change the, WHITE, O., KERLAVAGE, A. R., CLAYTON, R. A., SUTTON, G. G., FLEISCHMANN, R. D., KETCHUM, K. A., KLENK, H. P., GILL, S., DOUGHERTY, B. A., NELSON, K., QUACKENBUSH, J., ZHOU, L., KIRKNESS, E. F., PETERSON, S., LOFTUS, B., RICHARDSON, D., DODSON, R., … Venter, J. C. (2018). Enhanced Reader.pdf. In Nature (Vol. 388, pp. 539–547).
17. Dost, (B, Zednik, J., Havskov, J., Willemann, R. J., & Bormann, P. (n.d.). New Manual of Seismological Observatory Practice-NMSOP New Manual of Seismological Observatory Practice. https://doi.org/10.2312/GFZ.NMSOP_r1_ch1
18. Emry, E. L., Wiens, D. A., & Garcia-Castellanos, D. (2014). Journal of Geophysical Research : Solid Earth. AGU: Journal of Geophysical Research, Solid Earth, 119(iv), 3076–3095. https://doi.org/10.1002/2014JB011669.Received
19. Esposito, M., Marzorati, S., Belli, A., Ladina, C., Palma, L., Calamita, C., Pantaleo, D., & Pierleoni, P. (2024). Low-cost MEMS accelerometers for earthquake early warning systems: A dataset collected during seismic events in central Italy. Data in Brief, 53, 110174. https://doi.org/10.1016/j.dib.2024.110174
20. 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). https://doi.org/10.3390/s22062124
21. Grasso, V. F., Beck, J. L., & Manfredi, G. (2007). Automated decision procedure for earthquake early warning. Engineering Structures, 29(12), 3455–3463. https://doi.org/10.1016/j.engstruct.2007.08.020
22. Hou, B., Li, S., & Song, J. (2023). Support Vector Machine-Based On-Site Prediction for China Seismic Instrumental

Intensity from P-Wave Features. In Pure and Applied Geophysics (Vol. 180, Issue 10, pp. 3495–3515). https://doi.org/10.1007/s00024-023-03335-6
23. Jamalipour, A., Ansari, N., Howlader, M., & Xiao, C. X. C. (2005). Wireless communications. GLOBECOM '05. IEEE Global Telecommunications Conference, 2005., 6. https://doi.org/10.1109/GLOCOM.2005.1578357
24. Jiao, P., & Alavi, A. H. (2020). Artificial intelligence in seismology: Advent, performance and future trends. Geoscience Frontiers, 11(3), 739–744. https://doi.org/10.1016/j.gsf.2019.10.004
25. Kuyuk, H. S., Allen, R. M., Brown, H., Hellweg, M., Henson, I., & Neuhauser, D. (2014). Designing a network-based earthquake early warning algorithm for California: ElarmS-2. Bulletin of the Seismological Society of America, 104(1), 162–173. https://doi.org/10.1785/0120130146
26. Kuyuk, H. S., & Susumu, O. (2018a). Real-time classification of earthquake using deep learning. Procedia Computer Science, 140(November), 298–305. https://doi.org/10.1016/j.procs.2018.10.316
27. Kuyuk, H. S., & Susumu, O. (2018b). Real-time classification of earthquake using deep learning. Procedia Computer Science, 140, 298–305. https://doi.org/10.1016/j.procs.2018.10.316
28. McBride, S. K., Smith, H., Morgoch, M., Sumy, D., Jenkins, M., Peek, L., Bostrom, A., Baldwin, D., Reddy, E., De Groot, R., Becker, J., Johnston, D., & Wood, M. (2022). Evidence-based guidelines for protective actions and earthquake early warning systems. Geophysics, 87(1), WA77–WA102. https://doi.org/10.1190/geo2021-0222.1
29. Minson, S. E., Baltay, A. S., Cochran, E. S., Hanks, T. C., Page, M. T., McBride, S. K., Milner, K. R., & Meier, M. A. (2019). The Limits of Earthquake Early Warning Accuracy and Best Alerting Strategy. Scientific Reports, 9(1), 1–13. https://doi.org/10.1038/s41598-019-39384-y
30. Peng, C., Jiang, P., Ma, Q., Wu, P., Su, J., Zheng, Y., & Yang, J. (2021). Performance Evaluation of an Earthquake Early Warning System in the 2019–2020 M6.0 Changning, Sichuan, China, Seismic Sequence. Frontiers in Earth Science, 9. https://doi.org/10.3389/feart.2021.699941
31. Pinsky, V. (2015). Modeling warning times for the Israel's earthquake early warning system. Journal of Seismology, 19(1), 121–139. https://doi.org/10.1007/s10950-014-9454-z
32. Saad, O. M., Hafez, A. G., & Soliman, M. S. (2021). Deep Learning Approach for Earthquake Parameters Classification in Earthquake Early Warning System. IEEE Geoscience and Remote Sensing Letters, 18(7), 1293–1297. https://doi.org/10.1109/LGRS.2020.2998580
33. Sahin, A., Sisman, R., Askan, A., & Hori, M. (2016). Development of integrated earthquake simulation system for Istanbul the Next Marmara Earthquake: Disaster Mitigation, Recovery and Early Warning 4. Seismology. Earth, Planets and Space, 68(1). https://doi.org/10.1186/s40623-016-0497-y
34. Saraswathi, M., & Bhuvaneswari, T. (2013). Multitenancy in Cloud Software as a Service Application. International Journal of Advanced Research in Computer Science and Software Engineering.
35. Seo, J., Kim, Y., Ha, J., Kwak, D., Ko, M., & Yoo, M. (2024). Unsupervised anomaly detection for earthquake detection on Korea high-speed trains using autoencoder-based deep learning models. Scientific Reports, 14(1), 1–15. https://doi.org/10.1038/s41598-024-51354-7
36. Tajima, F., & Hayashida, T. (2018). Earthquake early warning: what does "seconds before a strong hit" mean? Progress in Earth and Planetary Science, 5(1). https://doi.org/10.1186/s40645-018-0221-6
37. Wagner, A., Blechschmidt, A. M., Bouarar, I., Brunke, E. G., Clerbaux, C., Cupeiro, M., Cristofanelli, P., Eskes, H., Flemming, J., Flentje, H., George, M., Gilge, S., Hilboll, A., Inness, A., Kapsomenakis, J., Richter, A., Ries, L., Spangl, W., Stein, O., … Zerefos, C. (2015). Evaluation of the MACC operational forecast system - Potential and challenges of global near-real-time modelling with respect to reactive gases in the troposphere. Atmospheric Chemistry and Physics, 15(24), 14005–14030. https://doi.org/10.5194/acp-15-14005-2015
38. Wu, Y.-M., & Kanamori, H. (2008). Development of an Earthquake Early Warning System Using Real-Time Strong Motion Signals. www.mdpi.org/sensors
39. Wu, Y. M., Hsiao, N. C., Lee, W. H. K., Teng, T. L., & Shin, T. C. (2007). State of the art and progress in the earthquake early warning system in taiwan. Earthquake Early Warning Systems, 283–306. https://doi.org/10.1007/978-3-540-72241-0_14
40. Wu, Y. M., & Kanamori, H. (2008). Development of an earthquake early warning system using real-time strong motion signals. Sensors, 8(1). https://doi.org/10.3390/s8010001
41. Wu, Y. M., Kanamori, H., Allen, R. M., & Hauksson, E. (2007). Determination of earthquake early warning parameters, τc and Pd, for southern California. Geophysical Journal International, 170(2), 711–717. https://doi.org/10.1111/j.1365-246X.2007.03430.x
42. Yu, Z., Sun, Y., Zhang, J., Zhang, Y., & Liu, Z. (2023). Gated recurrent unit neural network (GRU) based on quantile regression (QR) predicts reservoir parameters through well logging data. Frontiers in Earth Science, 11(January), 1–8. https://doi.org/10.3389/feart.2023.1087385
43. Zhang, M., Qiao, X., Seyler, B. C., Di, B., Wang, Y., & Tang, Y. (2021). Brief communication: Effective earthquake early warning systems: appropriate messaging and public awareness roles. Natural Hazards and Earth System Sciences, 21(10), 3243–3250. https://doi.org/10.5194/nhess-21-3243-2021
44. Zhang, W., & Huang, W. (n.d.). Applications of Fiber Optics Sensors in Seismology.