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Application of Artificial Intelligence and Machine Learning in Seismological Studies

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Abstract

Seismological studies have traditionally relied on classical statistical models and manual interpretation to detect, analyze, and predict earthquake events. However, the growing complexity and volume of seismic data have necessitated more efficient and adaptive approaches. This study explores the integration of artificial intelligence (AI) and machine learning (ML) techniques into seismology. This study highlighted the capacity of AI and ML to revolutionize seismic data processing and interpretation. Majorly, the study reviewed findings on algorithms such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs), support vector machines (SVMs), and unsupervised clustering methods. Also, AI systems such as WaveCastNet, SCALODEEP, BNGCNN, Cycle-Jnet, SASMEX, and UREDAS were reviewed in areas that improved accuracy in earthquake detection, earthquake predictions, and earthquake analysis.

Keywords: Artificial Intelligence (AI); Machine Learning (ML); Deep Learning (DL); Convolutional Neural Network (CNN).

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1. Introduction

The increasing frequency and devastating impact of earthquakes worldwide have prompted the urgent need for advancements in seismological monitoring, prediction, and hazard mitigation. Traditional methods in seismology, though reliable, often face limitations in processing the ever-growing volume of seismic data and capturing the complex, nonlinear patterns associated with earthquake phenomena. In recent years, the integration of artificial intelligence (AI) and machine learning (ML) into seismological studies has emerged as a transformative approach, enhancing the precision, efficiency, and depth of seismic data analysis [1, 2].

Artificial intelligence (AI) and machine learning (ML) have significantly advanced seismological studies, improving earthquake detection, prediction, and analysis. Artificial intelligence (AI) and machine learning (ML) are increasingly transforming the field of seismology by offering new ways to detect, analyze, and interpret seismic events [3]. Mostly, applications of AI and ML are closely related but have different concepts. Traditionally, seismological studies relied on manual analysis and statistical models to detect earthquakes and understand seismic wave behavior [4]. The contemporary issues in seismology problems like earthquake detection, phase picking, earthquake early warning (EEW), ground-motion prediction, seismic tomography, and earthquake geodesy [4-6]. The applications of AI and ML are illustrated in *Figure 1*.

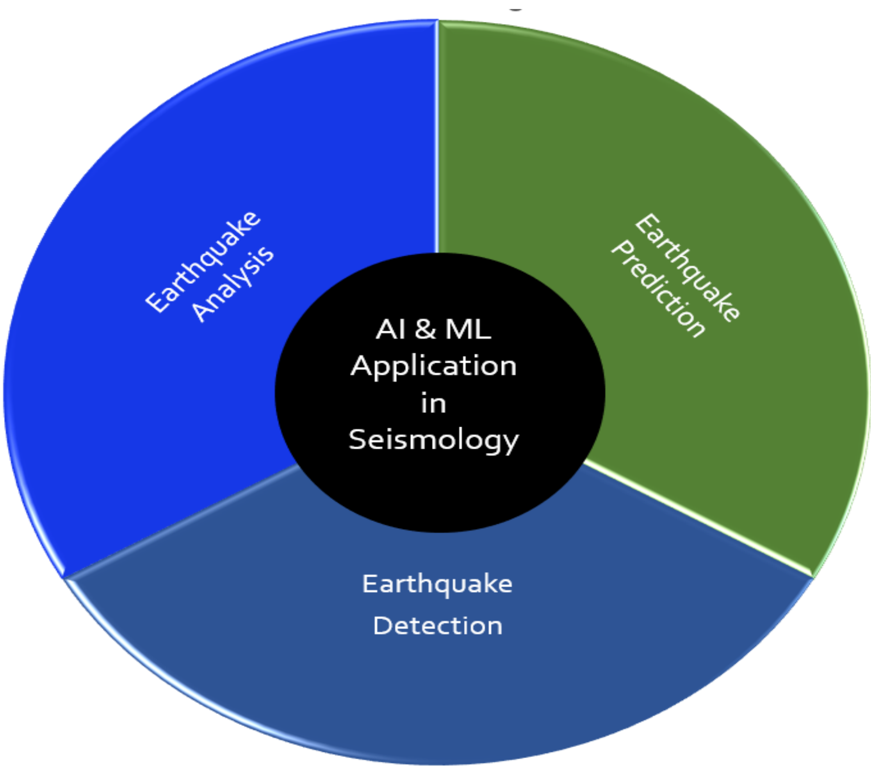

Figure 1: Application of AI and ML in Seismology

However, the surge in seismic data from global sensor networks has created an opportunity for AI and ML to provide more efficient and accurate tools for seismic analysis [7]. These technologies are now being applied in various aspects of seismology, including real-time earthquake detection, classification of seismic events, magnitude estimation, and seismic signal denoising [6-10]. AI-based models help identify unseen seismic signals, extract features, and enhance early warning systems [3, 9, 11-13]. Moreover, studies have highlighted the role of ML in developing earthquake catalogs, analyzing seismicity patterns, and improving geodetic data interpretation in seismological studies [3, 14, 15]. Additionally, machine learning models help analyze seismicity by identifying complex patterns in seismic activity, aiding in earthquake risk assessment and hazard predictions [16-18] . AI-driven algorithms have also enhanced ground-motion prediction, making intensity forecasts more reliable for engineers designing infrastructure in earthquake-prone regions [19, 20]. In crustal deformation studies, AI aids in detecting geodetic signals related to both seismic and aseismic processes, enriching technical understanding of tectonic movements and fault dynamics [19-21].

Seismic tomography is another technical area where AI and ML have improved. Seismic tomography is an imaging technique for studying the Earth's interior, and AI-assisted algorithms have enhanced in mapping of subsurface structures [22, 23]. These advancements, powered by AI and ML, transform seismology, making earthquake prediction, hazard mitigation, and risk assessment more precise and effective than ever before [24].

This review assesses the application of AI and ML in various areas of seismological studies and explorations. The literature synthesis from various articles includes AI models, ML algorithms, the area of application, technical contribution, and future considerations

2. Applications of Artificial Intelligence and Machine Learning in Seismology

AI and ML technologies, particularly deep learning models, have shown remarkable capabilities in various seismological tasks, such as automatic earthquake detection, seismic phase picking, event localization, magnitude estimation, and ground motion prediction [8, 9, 17, 25, 26]. These models are capable of learning from vast datasets and uncovering subtle features that conventional techniques might overlook [27]. Recently, convolutional neural networks (CNNs) have been applied successfully to improve the accuracy and speed of seismic phase identification, while recurrent neural networks (RNNs) have demonstrated potential in forecasting temporal seismic patterns [17, 22, 28]. Other useful and contributing DL models include transformers, generative adversarial networks (GANs) [20, 29]. Additionally, deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (especially long short-term memory [LSTM]) are effective at identifying patterns in complex waveform data, enabling faster and more reliable identification of earthquakes and related phenomena [29, 30]. Generative AI models are expected to be able to contribute to the field of seismology that is in generating text and image data [20].

On the other hand, the adaptability of ML models (supervised learning [SL], unsupervised learning [UL], and reinforcement learning [RL]) allows them to be trained across different geographical and tectonic settings, making them valuable tools for both global and regional seismic studies [3, 12, 16]. Moreover, ML algorithms, namely logistic regression, k-nearest neighbors, decision tree, random forest, AdaBoost, and gradient boosting, are trained using a dataset of nonlinear responses to rapidly analyze the initial seismic waves (P-waves) to predict the magnitude and potential impact of an earthquake (an enhancement for EEW) [12, 16, 19, 20]. Prevalently, most researchers employ deep learning models to predict earthquakes or earthquake forecasting based on either seismic wave characteristics or seismic activity data [19]. Also, AI models predict earthquake magnitude and depth using either logistic model tree and Bayesian network, which have the highest sensitivity, accuracy, and F-measure efficiency [19].

The increasing availability of open-source seismic datasets and computational resources has further accelerated research in this domain [14]. Despite these advancements, several challenges remain, such as the interpretability of AI-driven models, data quality variability, and the need for standardized evaluation benchmarks. Nonetheless, the integration of AI and ML into seismology marks a significant leap toward more accurate, efficient, and automated seismic monitoring and risk mitigation.

Hence, various contributions from published articles are evaluated with respect to their area of study, AI model, or ML model applied, and future prospects. The recent publication on the application of AI and ML is presented as follows.

Ge and colleagues established an AI-based prediction of seismic time-history responses of RC frame structures based on structural parameters [31]. They designed an end-to-end framework for intelligent seismic response prediction (ISRPnet) that comprises a structural parameter module for discretizing reinforced concrete frame structures into a series of static features and an encoder-decoder architecture for encoding seismic loads and autoregressively predicting seismic responses [31]. The model was trained on a data set of 16,544 cases generated through validated fibre-based finite element models, and it achieved an efficient performance on both frequent and rare earthquakes [31]. ISRPnet was reported to be more precise, faster, and efficient, especially for temporal responses for frequent earthquakes [31]. The predictions for the peak displacement for rare earthquakes were reported to be more accurate as well. In general, ISRPnet demonstrated superiority over traditional statistical models in the area of physical loss, “gated recurrent units over long short-term memory”, generalization, and extrapolation abilities of the model [31].

Reichstein and co-researchers investigated the potential of integrated artificial intelligence (AI) frameworks in advancing early warning systems for complex climate-related risks, including extreme weather events, wildfires, and geophysical hazards such as earthquakes. The methodology employed involves the integration of various AI techniques, which include neural networks (CNN, RNN, GAN, etc.), causality-based learning (RL, structural causal models [SCMs], counterfactual learning, debiased ML, etc.), and hybrid physics-informed models (Physics-informed neural networks [PINNs], with large-scale Earth system datasets encompassing satellite observations, climate reanalyses, and historical event records. They established that integrated AI systems improve forecasting accuracy, transparency, and actionable relevance of predictions, which is critical for risk communication and policy implementation in seismology [20].

Kubo and colleagues conducted a comprehensive overview of the recent progress made in the application of machine learning (ML) techniques to earthquake seismology. They highlighted how ML models are transforming traditional methods of seismic data analysis [14]. Their study is grounded in a detailed literature review that synthesizes a wide range of studies, categorizing ML applications into core areas such as earthquake detection, seismic phase picking, magnitude and location estimation, and tomographic imaging. The ML models studied were convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which have proven effective in handling complex, high-dimensional seismic data. They reported that ML models significantly outperform traditional seismological techniques in terms of speed, accuracy, and scalability [14]. Kubo and his colleagues reported that ML has facilitated the automation of real-time seismic monitoring, reducing reliance on manual intervention and improving response times in early warning systems.

Jia and Zhou explored the growing integration of machine learning (ML) technologies in the field of seismology, providing a thematic and methodological analysis of current trends, achievements, and challenges [32]. The research was a comparative analysis that expressed that ML models, particularly deep learning (DL) techniques, significantly improve the accuracy and automation of tasks like phase picking, earthquake cataloging, and fault detection. They established that CNN-based models outperformed traditional template matching techniques in detecting low-magnitude seismic events, while ML-driven regression models achieved superior results in estimating earthquake magnitudes and epicentral locations [32]. Furthermore, they emphasized how hybrid models that integrate domain knowledge with data-driven algorithms can enhance both performance and interpretability.

Satish and his colleagues developed and evaluated an AI-driven predictive model for earthquake forecasting by leveraging big data analytics to enhance the accuracy and reliability of seismic event predictions [33]. They utilized a range of machine learning (ML) and deep learning techniques, such as decision trees, support vector machines (SVMs), and long short-term memory (LSTM) networks, to model temporal and spatial patterns of seismic activity. Also, several methods that involved the pre-processing of large seismic datasets, feature engineering, model training and validation, and performance evaluation using metrics like root mean square error (RMSE), accuracy, and area under the curve (AUC) were applied [33]. They reported that LSTM-based models demonstrated superior performance in capturing temporal dependencies and forecasting seismic trends. Additionally, the outcome of AI models indicated that, when trained on large and diverse datasets, they can identify non-linear correlations and precursors that are often missed by traditional statistical models, thereby improving forecasting potential [33].

Lara investigated the application of artificial intelligence (AI) techniques in the detection of seismic signals, with a specific focus on the enhancement of real-time monitoring and signal classification accuracy [34]. The benchmark established was a combination of supervised learning (SL) approaches and neural network (NN) architectures, which was convolutional neural networks (CNNs). The research examines model training on labeled seismic datasets and tests their performance across different geographic regions, signal types, and noise types. Lara reported that AI models, especially CNNs, consistently outperform traditional rule-based or thresholding techniques, particularly in low signal-to-noise ratio environments [34].

Ibrahim and Al-Bander established an effective framework that integrates geospatial analysis, ML, and statistical modeling to analyze global earthquake patterns and improve seismic risk assessment [24]. The researchers applied clustering techniques (such as K-means and Density-Based Spatial Clustering of Applications with Noise [DBSCAN]) to identify spatiotemporal patterns, followed by the use of supervised learning algorithms like support vector machines (SVM) and decision trees to classify risk levels and predict future seismic events [24]. Moreover, geographic information systems (GIS) were employed to visualize seismic zones and assess regional vulnerability by overlaying seismic activity with population density and infrastructure data. They reported that the integrated model significantly improves the accuracy of seismic risk classification and highlights high-risk zones that were underrepresented in traditional models [24]. The framework also reveals new insights into global seismic trends, such as emergent clusters of activity in previously overlooked areas.

Marano and colleagues conducted an extensive study on the application of generative adversarial networks (GANs) in earthquake-related engineering disciplines to highlight the growing relevance of synthetic data generation in seismic modelling, structural health monitoring, and earthquake damage simulation [29]. The study used a systematic review to analyze over 150 publications and technical reports that detail the deployment of GANs across various subfields such as seismic wave simulation, structural response modeling, image-based damage classification, and synthetic ground motion generation [29]. The authors highlighted that GANs are particularly effective in generating high-fidelity synthetic data to train deep learning models, thereby addressing data imbalance and improving generalizability in earthquake engineering applications [29]. Additionally, the results indicated that GANs have significantly advanced several earthquake engineering applications by enabling realistic simulations of rare seismic events and improving the robustness of AI-based structural assessments. However, Marani and his colleagues established that GAN-generated data may introduce biases or artifacts that can mislead model interpretation if not properly validated [29].

Lyu and colleagues introduced WaveCastNet, a novel artificial intelligence framework designed to forecast seismic wavefields in real time, aimed at enhancing the speed and accuracy of earthquake early warning (EEW) systems [35]. The innovative tech was driven by the limitations of conventional numerical solvers, which, while accurate, are computationally expensive and often too slow for practical early warning applications. The AI tech was based on a physics-guided deep learning architecture that leverages past seismic wavefield recordings to predict future ground motions across a spatial grid [35]. The model is trained and validated using high-resolution synthetic simulations generated from 3D finite-difference methods, which provide diverse earthquake scenarios for robust generalization [35]. The researchers established that WavecastNet can forecast wavefields with high fidelity several seconds into the future, well within the decision-making window needed for early warnings. Furthermore, the comparison with the traditional numerical solvers, WaveCastNet, offers significantly faster inference speeds without compromising prediction quality [35].

Jia and Ye carried out a comprehensive review on the application of deep learning techniques in earthquake disaster assessment, offering a structured framework that categorizes research progress across key elements [17]. The study covered over 100 recent publications and case studies that involve the use of deep learning in various stages of earthquake disaster management, ranging from rapid damage detection and impact mapping to long-term recovery assessment. They identify the most commonly used data types (e.g., satellite imagery, unmanned aerial vehicle (UAV) data, and crowdsourced information), deep learning architectures (such as convolutional neural networks [CNNs], recurrent neural networks [RNNs], and generative adversarial networks [GANs]), and assessment objectives (e.g., building collapse detection, infrastructure damage classification, and casualty estimation) [17]. Jia and Ye highlighted that while deep learning has significantly improved the speed and granularity of post-earthquake assessments, key limitations persist, particularly concerning data availability, model transferability across regions, and the lack of standardized benchmarks [17].

Mousavi and Beroza demonstrated the revolutionary impact of deep learning in the field of seismology as an alternative in signal processing and modelling techniques [10]. They presented a conceptual and application-based overview of deep-learning methods, particularly CNNs, RNNs, and transformer-based architectures, being adopted to address fundamental challenges in seismic data analysis. Mousavi and Beroza stated that the DL architectures mentioned above have achieved state-of-the-art performance in real-time earthquake detection, seismic phase picking, microseismicity detection, and ground motion forecasting. Additionally, the implementation of deep networks has enhanced earthquake early warning systems by reducing detection latency and increasing robustness to noise [10].

Aden-Antoniów and his colleagues assessed the challenges in seismology in the area of declustering earthquake catalogues by introducing a novel machine learning approach based on random forest algorithms [6]. The study focused on distinguishing between the background seismicity from aftershocks and other clustered events using a data-driven, probabilistic model that is more flexible and adaptable than traditional statistical methods, such as the Reasenberg or Gardner-Knopoff algorithms [6]. The methodology centers on training a supervised random forest classifier on synthetic earthquake catalogs, which simulate a wide range of clustering behaviors and tectonic conditions. They reported that the random forest model can effectively separate clustered events from background seismicity with greater precision than conventional rule-based techniques [6]. Importantly, the model provides probabilistic scores rather than binary classifications, allowing for more nuanced interpretations.

Bilal and his colleagues introduced an innovative deep learning framework for early earthquake detection using a Batch Normalization Graph Convolutional Neural Network (BNGCNN) to improve the accuracy and speed of seismic event identification [36]. The benchmark was designed to convert seismic waveform data into graph representations, where nodes correspond to seismic stations and edges encode spatial or functional proximity [36]. The BNGCNN was trained on labeled seismic data, using features derived from the waveform’s temporal dynamics. Moreover, batch normalization layers were employed to stabilize learning and accelerate convergence. The model's performance is benchmarked against existing deep learning methods using metrics such as accuracy, precision, recall, and F1-score. The BNGCNN outperformed the traditional CNNs and vanilla graph convolutional networks, particularly in noisy environments and when processing large-scale sensor data [36].

Saad and his colleagues introduced *Scalodeep*, a scalable and highly generalized deep learning framework designed to enhance real-time earthquake detection across diverse seismic environments [9]. *Scalodeep* is based on a convolutional neural network (CNN) architecture trained on a large, heterogeneous dataset encompassing various geophysical settings, waveform types, and noise conditions [9]. *Scalodeep* was trained using over 5 million waveform samples using supervised learning, with an emphasis on augmenting data diversity to improve generalization. *Scalodeep* achieved state-of-the-art accuracy, sensitivity, and low false detection rates across multiple seismic networks. Also, it outperformed both traditional detection algorithms and earlier deep learning models [9]. Crucially, the model was reported to be computationally efficient, supporting real-time seismic monitoring applications with low-latency responses.

Ma and Mei performed an in-depth and systematic review of the role of deep learning in geological hazard analysis, encompassing earthquake prediction, landslide detection, and hazard risk mapping [30]. The methodology was based on a structured review of over 150 publications covering four main dimensions: data sources, deep learning models, applications, and existing bottlenecks. The study demonstrated that deep learning models have significantly outperformed traditional statistical and machine learning methods in terms of predictive accuracy and scalability, especially when dealing with high-dimensional and unstructured geospatial datasets [30]. Ma and Mei emphasized on earthquakes, indicating that DL has been particularly impactful in early warning systems, seismic signal classification, and ground motion prediction. However, the authors caution that issues such as data imbalance, lack of standardized benchmarks, and the "black-box" nature of deep learning still pose barriers to widespread operational deployment.

Mousavi and Beroza addressed the limitations of traditional methods for earthquake magnitude estimation by introducing a machine learning-based framework designed to improve speed and accuracy [10]. They specifically focused on leveraging DL techniques to estimate earthquake magnitudes directly from raw seismic waveforms, bypassing the reliance on empirical amplitude-based relationships that often underperform in complex seismic environments [10]. Mousavi and Beroza established that CNN architecture has the capability of learning discriminative features from waveform segments to predict magnitudes with higher consistency. The results demonstrate that the proposed machine learning model outperforms traditional magnitude estimation methods, particularly in cases where signal quality is limited or data is incomplete.

Min and his colleagues introduced an innovative method to provide noise removal from seismic data by adopting a deep denoising autoencoder (DDAE), which is a convolutional autoencoder (CAE) integrated with a GAN framework (DDAE-GAN) in a three-step procedure [37]. The model was designed to incorporate a generative adversarial network (GAN) to generate a large number of paired clean-noisy data using real noise [37]. Additionally, a deep denoising autoencoder (DDAE) was pre-trained using GAN-generated data, and a transfer learning technique was used to train the DDAE further on a few field datasets. They reported that the method was able to suppress seismic data noise well [37].

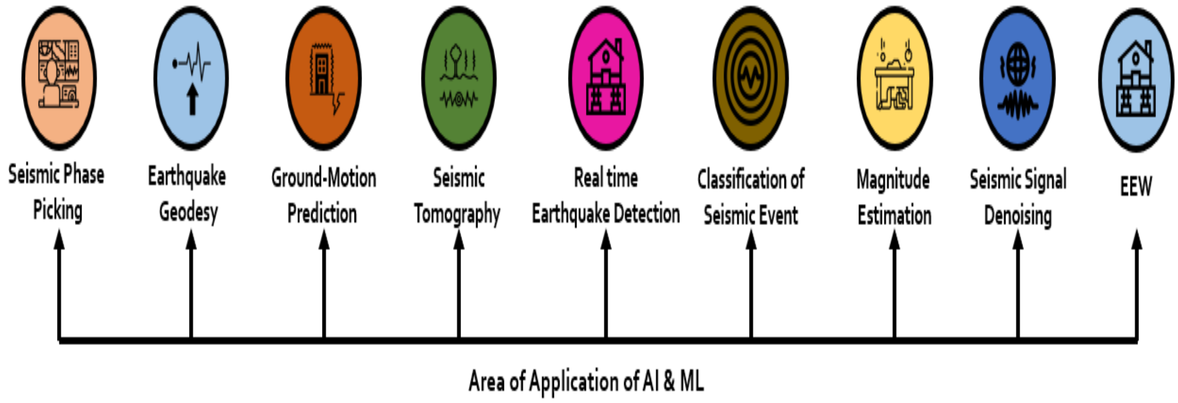

Figure 2: Area of Applications of AI and ML in Seismology

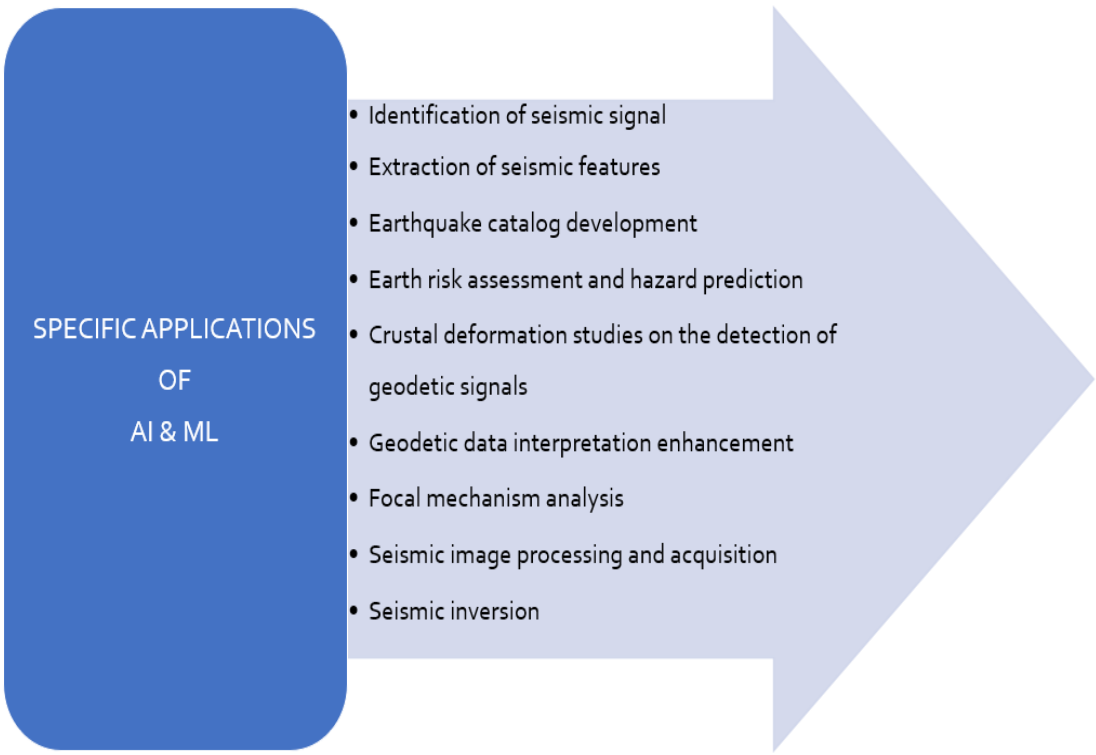

Figure 3: Specific Application of AI and ML in Seismology

Table 1: List of Frameworks and Models of AI and ML in Seismology

S/N	Framework / Model	Type	Application of ML & AI
1	CNN	ML	Seismic phase identification[17, 22, 26, 38, 39], real-time earthquake detection and identification [29, 30], estimation of earthquake magnitudes &EEW [17, 29, 32, 40], seismic phase picking, and ground motion forecasting [26, 30]
2	RNN	ML	Forecasting temporal seismic patterns [17, 22, 28], earthquake detection [20, 29, 30], seismic phase picking, microseismicity detection [26]
3	GAN	ML	Earthquake damage simulation [29, 41], seismic denoising [17, 32], earthquake classification [24]
4	ISRPnet	AI	Seismic prediction [31]
5	SCMs	AI	Early earthquake warning system [20]
6	PINNs	ML	Early earthquake warning system[20], earthquake detection [14]
7	SVMs	AI	Earthquake forecasting, earthquake detection, phase picking, EEW, ground-motion prediction, seismic tomography, and earthquake geodesy. [3, 12, 42]
8	WaveCastNet	AI	EEW, ground-motion prediction [13, 35]
9	SCALODEEP	AI	Real-time seismic monitoring and earthquake detection [43]
10	BNGCNN	AI	Early earthquake detection [36]
11	Cycle-Jnet	AI	Identification of geological features [44]
12	UREDAS	AI	Earthquake magnitude estimation [45].
13	SASMEX	ML	Early earthquake detection and EEW[46].
14	CycleGAN		Artificially decimated images and earthquake analysis [47]
15	SAGAN		Earthquake analysis [48]
16	ANN	ML	Earthquake detection, phase picking, EEW, ground-motion prediction, seismic tomography, and earthquake geodesy. [3, 42]
17	Random Forest	ML	Earthquake classification [49]
18	DeepShak	ML	Earthquake prediction [50]
19	Autoencoder	ML	Seismic denoising [51]
20	DDAE	ML	Seismic denoising [37]

3. Discussion on Future Applications of AI and ML

So far, AI and ML models have demonstrated much potential in seismological enhancement. Also, Al and ML have influenced transformation and optimization in areas like early warning systems, tectonic movement, and fault dynamics. The prospect of improving and establishing systems with the capacity to learn from high-dimensional data, adapt across spatial-temporal scales, and bridge empirical data with domain theory is still paramount. Challenges persist in earthquake precise prediction, ground motion prediction, real-time earthquake monitoring, limitations in seismic tomography, and data imbalance & noise. Jia and Ye [17] established that deep learning has significantly improved the speed and granularity of post-earthquake assessments, even though key limitations persist, particularly concerning data availability, model transferability across regions, and the lack of standardized benchmarks. Ma and Mei [30] established that due to the complexity of deep learning and the uncertainty of geological hazards, the application of deep learning in geological hazard analysis poses numerous challenges while generating broader opportunities. The issues are data imbalance, lack of standardized benchmarks, and the "black-box" nature of deep learning still pose barriers to widespread operational deployment. Although, deep learning models have significantly outperformed traditional statistical and machine learning methods in terms of predictive accuracy and scalability, especially when dealing with high-dimensional and unstructured geospatial datasets [30]. Researching these challenges is essential due to challenges that persist, particularly in ensuring model robustness, addressing data gaps in low-income regions, and maintaining ethical standards in algorithm design and deployment.

Based on the persistent challenges, Reichstein and his colleagues recommended expanding interdisciplinary collaborations to co-design AI models with stakeholders, especially by embedding uncertainty quantification within predictive systems and investing in open data infrastructures that support inclusive and global risk assessment [20]. Kubo and his colleagues emphasized that deep learning, especially CNN and RNN, has a promising influence in resolving these challenges [14]. Kubo and his colleagues established that DL models have demonstrated outstanding performance and have greatly improved the accuracy of automatic processing, especially in ground-motion data modeling, analysis of geodetic data related to crustal deformation, and detection of geodetic signals caused by seismic/aseismic phenomena [14]. Bilal and his colleagues established that the experimental findings using DL indicated that the batch normalization with graph convolutional neural networks (BNGCNN) surpasses existing models, suggesting its potential utility in real-time earthquake monitoring systems [36].

Mousavi and Beroza [26] validated that deep-learning models systematically outperform classical characteristic function-based models, especially with much lower computational cost and no need for template events. Also, deep-learning models generalize well to other regions or data types beyond their training data, and compared with the classical methods. Deep-learning models perform better in conditions with a lower signal-to-noise ratio (SNR). Mousavi and Beroza [26] futurized that DNNs will be capable of performing multiple seismic data analyses, notwithstanding issues of interpretability and brittleness Liu, and his colleagues [41] stated using DL accelerated prestack time migration by more than 100 times, and Kaur, and his colleagues [38] reported that DL improved both computational efficiency and image resolution in least-squares migration by estimating the inverse Hessian operator when a cyclic GAN is used.

Additionally, Kaur and his colleagues established that the feature-learning and dimensionality-reduction abilities of CNNs are well suited for clustering of seismic response in terms of geological properties and outperform machine-learning approaches for seismic facies mapping based on hand-engineered features, a fact that was similarly established by Qian and his colleagues in 2018 [52, 53]. For noise issues in seismic data, Yi and his colleagues and Feng and his colleagues stated that an effective approach to meet this challenge is to create semisynthetic data in which clean synthetic signals are combined with manually picked noise from the field data [54, 55]. Xu, and his colleagues [56] proposed an automatic P-wave onset time picking method for mining-induced microseismic data based on a long short-term memory deep neural network. The proposed method will accurately extract data features of micro seismic waveforms and further improve the P-onset picking performance. Moreover, Xie, and his colleagues [57] exploited GAN to perform fast noise removal on onshore land seismic data, attempting to provide a new technology for real-time processing.

In contrast to DL, transfer learning is another potential solution that has been specified among researchers. Kubo, and his colleagues [14] stated that effective approaches to address earthquake seismology problems include data augmentation, simultaneous use of domain knowledge, and transfer learning. They went further, stating that applying the latest techniques, such as PINNs, neural operators, Bayesian neural network (BNN), and explainable artificial intelligence (XAI), can address challenges that arise from the black-box nature of DL.

Jia and Zhou [58] highlighted the limitations of ML models and that future works should focus on enhancing model accuracy and generalizability, the development of real-time applications in seismology, and the exploration of the physical mechanisms underlying earthquakes through machine learning methodologies. Zhu and his colleagues suggested that a potential approach to address this issue (one of the challenges- earthquake monitoring) is the earthquake catalog development in aspects like waveform search processes, vast ML modelling, and optimization of complex systems using an end-to-end approach architecture (a neural network) [59]. In support of Zhu and his colleagues report, Woollam and his colleaguesand Tan and his colleagues also established that the development of an earthquake catalog is essential, which will contribute to resolving these challenges [60, 61]. Additionally, seismic datasets for retraining should ideally be publicly accessible and easily applicable for future model development, like the Seisbench toolbox [60]. Wang and his colleagues also supported futuristic influence of ML stating that “small earthquakes contain valuable predictive information”, underscoring the promise of machine learning in improving earthquake prediction accuracy [62].

For AI, Johora, and his colleagues [63] established that through the incorporation of seismic wave velocity data, the ANN models exhibit enhanced predictability compared to traditional multilinear regression models, thereby demonstrating the potential for increased efficiency and accuracy in geotechnical evaluations. Satish, and his colleagues [33] established that various AI models are centered on deep learning and work the “black boxes” given that predictions are minus pure descriptions of them inwards at those ends.

Artificial Intelligence (AI) provides a promising alternative approach for modeling ground motion propagation and the black-box issue because deep neural networks are well-suited to model the nontrivial spatiotemporal properties of ground motions [64]. Reichstein, and his colleagues [65] highlighted that AI has the potential to transform early warning systems into a sophisticated and enhanced system using high-dimensional data, adapted from spatial-temporal scales, and bridge empirical data. Additionally, Lyu, and his colleagues [35] highlighted that AI-enabled wavefield predictions have the potential to complement existing EEW techniques, particularly in high-risk seismic regions where every second matters.

5. Conclusion

The application of AI and ML in seismological studies has made potential impacts and transformative advancements in the field of geoscience and engineering. These intelligent systems have demonstrated significant capabilities in enhancing the detection, classification, and prediction of seismic events. Moreover, AI and ML have outperformed traditional seismological approaches in areas of seismic phase picking, seismic denoising, ground motion predictions, and seismic magnitude estimation. Another enhancement of AI and ML models is their capability to process and analyze massive volumes of seismic data in real time, identify hidden patterns, and learn complex relationships that are relatively complex to human experts.

From enhancing early warning systems to automating earthquake location and magnitude estimation, AI-driven techniques such as deep neural networks (CNN, RNN, GAN, etc.), support vector machines, and unsupervised clustering have proven to be more efficient, accurate, and adaptive. Furthermore, AI and ML have enabled the integration of various data sources, such as satellite imagery, GPS readings, and environmental sensors, to provide a holistic and multidimensional understanding of seismic activities.

However, despite their remarkable potential, the application of AI and ML in seismology is not without challenges. Issues such as black-box, model interpretability, data quality, lack of labeled training datasets, and the need for domain-specific tuning remain key hurdles. To address these, continued collaboration between seismologists, data scientists, and geotechnical professionals is paramount.

In conclusion, AI and ML are substantial tools that revolutionize seismological research and disaster management. As technology continues to evolve, the integration of AI and ML will become more efficient in mitigating earthquake risks, protecting infrastructure, and ultimately saving lives.

6. List of Abbreviations

AI	Artificial intelligence
ML	Machine learning
EEW	Earthquake early warning
CNN	Convolutional Neural Networks
RNN	Recurrent neural networks
DL	Deep learning
LSTM	Long short-term memory
SL	Supervised learning
UL	Unsupervised learning
RL	Reinforcing Learning

ISRPnet	Intelligent seismic response prediction
GAN	Generative Adversarial network
SCMs	Structural causal models
PINNs	Physics-informed neural networks
SVMs	Support vector machines
AUC	Area under the curve
RMSE	Root means square error
NN	Neural Network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
GIS	Geographic information systems
UAV	Unmanned area vehicle
BNGCNN	Batch Normalization Graph Convolutional Neural Network
XAI	Explainable Artificial Intelligence
BNN	Bayesian Neural Network

References

[1] K. J. Bergen, P. A. Johnson, M. V. de Hoop, and G. C. Beroza, "Machine learning for data-driven discovery in solid Earth geoscience," *Science,* vol. 363, no. 6433, p. eaau0323, 2019.

[2] Q. Kong, D. T. Trugman, Z. E. Ross, M. J. Bianco, B. J. Meade, and P. Gerstoft, "Machine learning in seismology: Turning data into insights," *Seismological Research Letters,* vol. 90, no. 1, pp. 3-14, 2019.

[3] H. K. Dadhich, "Overview of Artificial Intelligence (AI) and Machine Learning (ML) in Seismology," in *Geohazards: Analysis, Modelling and Forecasting*, Sandeep, P. Kumar, H. Mittal, and R. Kumar Eds. Singapore: Springer Nature Singapore, 2023, pp. 185-193.

[4] S. Stein and M. Wysession, *An introduction to seismology, earthquakes, and earth structure*. John Wiley & Sons, 2009.

[5] R. Kumar, H. Mittal, Sandeep, and B. Sharma, "Earthquake Genesis and Earthquake Early Warning Systems: Challenges and a Way Forward," *Surveys in Geophysics,* vol. 43, no. 4, pp. 1143-1168, 2022/08/01 2022, doi: 10.1007/s10712-022-09710-7.

[6] F. Aden-Antoniów, W. B. Frank, and L. Seydoux, "An Adaptable Random Forest Model for the Declustering of Earthquake Catalogs," *Journal of Geophysical Research: Solid Earth,* vol. 127, no. 2, p. e2021JB023254, 2022, doi: https://doi.org/10.1029/2021JB023254.

[7] P. Jiao and A. H. Alavi, "Artificial intelligence in seismology: Advent, performance and future trends," *Geoscience Frontiers,* vol. 11, no. 3, pp. 739-744, 2020/05/01/ 2020, doi: https://doi.org/10.1016/j.gsf.2019.10.004.

[8] M. S. Abdalzaher, H. A. Elsayed, and M. M. Fouda, "Employing Remote Sensing, Data Communication Networks, AI, and Optimization Methodologies in Seismology," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 15, pp. 9417-9438, 2022, doi: 10.1109/JSTARS.2022.3216998.

[9] O. M. Saad *et al.*, "SCALODEEP: A Highly Generalized Deep Learning Framework for Real-Time Earthquake Detection," *Journal of Geophysical Research: Solid Earth,* vol. 126, no. 4, p. e2020JB021473, 2021, doi: https://doi.org/10.1029/2020JB021473.

[10] S. M. Mousavi and G. C. Beroza, "A Machine-Learning Approach for Earthquake Magnitude Estimation," *Geophysical Research Letters,* vol. 47, no. 1, p. e2019GL085976, 2020, doi: https://doi.org/10.1029/2019GL085976.

[11] R. Lamsal and T. V. V. Kumar, "Artificial Intelligence and Early Warning Systems," in *AI and Robotics in Disaster Studies*, T. V. V. Kumar and K. Sud Eds. Singapore: Springer Nature Singapore, 2020, pp. 13-32.

[12] U. V. Anbazhagu, R. Sonia, R. K. Grover, E. A. Banu, C. Jothikumar, and M. Sudhakar, "AI and Machine Learning in Earthquake Prediction: Enhancing Precision and Early Warning Systems," in *Modern SuperHyperSoft Computing Trends in Science and Technology*, F. Smarandache and P. Majumder Eds. Hershey, PA, USA: IGI Global, 2025, pp. 1-32.

[13] Z. Ying, W. Congcong, S. Didier, and Z. Chengxiang, "Integrating Artificial Intelligence and Geophysical Insights for Earthquake Forecasting: A Cross-Disciplinary Review," *arXiv preprint arXiv:2502.12161,* 2025.

[14] H. Kubo, M. Naoi, and M. Kano, "Recent advances in earthquake seismology using machine learning," *Earth, Planets and Space*, vol. 76, no. 1, p. 36, 2024/02/28 2024, doi: 10.1186/s40623-024-01982-0.

[15] M. Sylvander *et al.*, "Seismicity patterns in southwestern France," (in en), *Comptes Rendus. Géoscience,* vol. 353, no. S1, pp. 79-104, 2021, doi: 10.5802/crgeos.60.

[16] P. Kourehpaz and C. M. Hutt, "Machine Learning for Enhanced Regional Seismic Risk Assessments," *Journal of Structural Engineering,* vol. 148, no. 9, p. 04022126, 2022, doi: doi:10.1061/(ASCE)ST.1943-541X.0003421.

[17] J. Jia and W. Ye, "Deep Learning for Earthquake Disaster Assessment: Objects, Data, Models, Stages, Challenges, and Opportunities," *Remote Sensing,* vol. 15, no. 16, p. 4098, 2023. [Online]. Available: https://www.mdpi.com/2072-4292/15/16/4098.

[18] A. Chitkeshwar, "The Role of Machine Learning in Earthquake Seismology: A Review," *Archives of Computational Methods in Engineering,* vol. 31, no. 7, pp. 3963-3975, 2024/09/01 2024, doi:

10.1007/s11831-024-10099-2.

[19] P. Kolivand *et al.*, "A systematic review of Earthquake Early Warning (EEW) systems based on Artificial Intelligence," *Earth Science Informatics,* vol. 17, no. 2, pp. 957-984, 2024/04/01 2024, doi: 10.1007/s12145-024-01253-2.

[20] M. Reichstein *et al.*, "Early warning of complex climate risk with integrated artificial intelligence," *Nature Communications,* vol. 16, no. 1, p. 2564, 2025/03/15 2025, doi: 10.1038/s41467-025-57640-w.

[21] Y. An *et al.*, "Current state and future directions for deep learning based automatic seismic fault interpretation: A systematic review," *Earth-Science Reviews,* vol. 243, p. 104509, 2023/08/01/ 2023, doi: https://doi.org/10.1016/j.earscirev.2023.104509.

[22] M. Shakeel, K. Itoyama, K. Nishida, and K. Nakadai, "Detecting earthquakes: a novel deep learning-based approach for effective disaster response," *Applied Intelligence,* vol. 51, no. 11, pp. 8305-8315, 2021/11/01 2021, doi: 10.1007/s10489-021-02285-7.

[23] N. Yousefpour and F. F. and Mojtahedi, "Early detection of internal erosion in earth dams: combining seismic monitoring and convolutional AutoEncoders," *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards,* vol. 18, no. 3, pp. 570-590, 2024/07/02 2024, doi: 10.1080/17499518.2023.2251128.

[24] M. Ibrahim and B. Al-Bander, "An integrated approach for understanding global earthquake patterns and enhancing seismic risk assessment," *International Journal of Information Technology,* vol. 16, no. 4, pp. 2001-2014, 2024/04/01 2024, doi: 10.1007/s41870-024-01778-1.

[25] H. Mai, "Developing Deep Learning Tools in Earthquake Detection and Phase Picking," Université d'Ottawa/University of Ottawa, 2023.

[26] S. M. Mousavi and G. C. Beroza, "Deep-learning seismology," *Science,* vol. 377, no. 6607, p. eabm4470, 2022.

[27] W. Zhu and G. C. Beroza, "PhaseNet: a deep-neural-network-based seismic arrival-time picking method," *Geophysical Journal International,* vol. 216, no. 1, pp. 261-273, 2019.

[28] Z. E. Ross, M. A. Meier, E. Hauksson, and T. H. Heaton, "Generalized seismic phase detection with deep learning," *Bulletin of the Seismological Society of America,* vol. 108, no. 5A, pp. 2894-2901, 2018.

[29] G. C. Marano, M. M. Rosso, A. Aloisio, and G. Cirrincione, "Generative adversarial networks review in earthquake-related engineering fields," *Bulletin of Earthquake Engineering,* vol. 22, no. 7, pp. 3511-3562, 2024/05/01 2024, doi: 10.1007/s10518-023-01645-7.

[30] Z. Ma and G. Mei, "Deep learning for geological hazards analysis: Data, models, applications, and opportunities," *Earth-Science Reviews*, vol. 223, p. 103858, 2021/12/01/ 2021, doi: https://doi.org/10.1016/j.earscirev.2021.103858.

[31] K. Ge, Y. T. Guo, C. Wang, and Z. Z. Hu, "AI-based prediction of seismic time-history responses of RC frame structures considering varied structural parameters," *Journal of Building Engineering*, vol. 106, p. 112643, 2025/07/15/ 2025, doi: https://doi.org/10.1016/j.jobe.2025.112643.

[32] K. Jia and S. Zhou, "Machine Learning Applications in Seismology," *Applied Sciences*, vol. 14, no. 17, p. 7857, 2024. [Online]. Available: https://www.mdpi.com/2076-3417/14/17/7857.

[33] S. Satish *et al.*, "AI-Driven Predictive Models for Earthquake Forecasting Using Big Data Analytics," *Available at SSRN 4981337*, 2024.

[34] P. E. Lara, "Detection of seismic signals by artificial intelligence," Université Côte d'Azur, 2024.

[35] D. Lyu *et al.*, "Wavecastnet: an AI-enabled wavefield forecasting framework for earthquake early warning," *arXiv preprint arXiv:2405.20516*, 2024.

[36] M. A. Bilal, Y. Ji, Y. Wang, M. P. Akhter, and M. Yaqub, "Early Earthquake Detection Using Batch Normalization Graph Convolutional Neural Network (BNGCNN)," *Applied Sciences*, vol. 12, no. 15, p. 7548, 2022. [Online]. Available: https://www.mdpi.com/2076-3417/12/15/7548.

[37] F. Min, L.-R. Wang, S.-L. Pan, and G.-J. Song, "DDAE-GAN: Seismic Data Denoising by Integrating Autoencoder and Generative Adversarial Network," Cham, 2021: Springer International Publishing, in Rough Sets, pp. 44-56.

[38] H. Kaur, N. Pham, and S. Fomel, "Improving the resolution of migrated images by approximating the inverse Hessian using deep learning," *Geophysics*, vol. 85, no. 4, pp. WA173-WA183, 2020.

[39] Z. Ross, M.-A. Meier, E. Hauksson, and T. Heaton, "Generalized Seismic Phase Detection with Deep Learning," *Bulletin of the Seismological Society of America*, vol. 108, 08/21 2018, doi: 10.1785/0120180080.

[40] R. Jena *et al.*, "Earthquake hazard and risk assessment using machine learning approaches at Palu, Indonesia," *Science of The Total Environment*, vol. 749, p. 141582, 2020/12/20/ 2020, doi: https://doi.org/10.1016/j.scitotenv.2020.141582.

[41] W. Liu, Q. Cheng, L. Liu, Y. Wang, and J. Zhang, "Accelerating high-resolution seismic imaging by using deep learning," *Applied Sciences*, vol. 10, no. 7, p. 2502, 2020.

[42] A. Kundu, Y. S. Bhadauria, S. Basu, and S. Mukhopadhyay, "Application of ANN and SVM for identification of tsunamigenic earthquakes from 3-component seismic data," in *2017 2nd IEEE*

International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), 19-20 May 2017 2017, pp. 10-13, doi: 10.1109/RTEICT.2017.8256549.

[43] S. M. Mousavi, W. Zhu, Y. Sheng, and G. C. Beroza, "CRED: A deep residual network of convolutional and recurrent units for earthquake signal detection," *Scientific reports*, vol. 9, no. 1, p. 10267, 2019.

[44] M. Tang, B. Huang, R. Xie, and Z. Chen, "A seismic inversion method based on multi-scale super-asymmetric cycle-jnet network," *Applied Sciences,* vol. 14, no. 1, p. 242, 2023.

[45] Y. Nakamura, J. Saita, and T. Sato, "On an earthquake early warning system (EEW) and its applications," *Soil Dynamics and Earthquake Engineering,* vol. 31, no. 2, pp. 127-136, 2011.

[46] G. Suárez, "The seismic early warning system of Mexico (SASMEX): A retrospective view and future challenges," *Frontiers in Earth Science,* vol. 10, p. 827236, 2022.

[47] H. Kaur, N. Pham, and S. Fomel, "Seismic data interpolation using CycleGAN," in *SEG technical program expanded abstracts 2019*: Society of Exploration Geophysicists, 2019, pp. 2202-2206.

[48] H. Zhang, I. Goodfellow, D. Metaxas, and A. Odena, "Self-attention generative adversarial networks," in *International conference on machine learning,* 2019: PMLR, pp. 7354-7363.

[49] M. Fernández-Delgado, E. Cernadas, S. Barro, and D. Amorim, "Do we need hundreds of classifiers to solve real world classification problems?," *The journal of machine learning research,* vol. 15, no. 1, pp. 3133-3181, 2014.

[50] A. Datta, D. J. Wu, W. Zhu, M. Cai, and W. L. Ellsworth, "DeepShake: Shaking intensity prediction using deep spatiotemporal RNNs for earthquake early warning," *Seismological Society of America,* vol. 93, no. 3, pp. 1636-1649, 2022.

[51] H. Zhou, Y. Guo, and K. Guo, "Seismic random noise attenuation using a tied-weights autoencoder neural network," *Minerals,* vol. 11, no. 10, p. 1089, 2021.

[52] F. Qian, M. Yin, X.-Y. Liu, Y.-J. Wang, C. Lu, and G.-M. Hu, "Unsupervised seismic facies analysis via deep convolutional autoencoders," *Geophysics,* vol. 83, no. 3, pp. A39-A43, 2018.

[53] Y. Duan, X. Zheng, L. Hu, and L. Sun, "Seismic facies analysis based on deep convolutional embedded clustering," *Geophysics,* vol. 84, no. 6, pp. IM87-IM97, 2019.

[54] Q. Feng and Y. Li, "Denoising deep learning network based on singular spectrum analysis—DAS seismic data denoising with multichannel SVDDCNN," *IEEE Transactions on Geoscience and Remote Sensing,* vol. 60, pp. 1-11, 2021.

[55] Y. Li, H. Wang, and X. Dong, "The denoising of desert seismic data based on cycle-GAN with unpaired data training," *IEEE Geoscience and Remote Sensing Letters,* vol. 18, no. 11, pp. 2016-2020, 2020.

[56] H. Xu, Y. Zhao, T. Yang, S. Wang, Y. Chang, and P. Jia, "An automatic P-wave onset time picking method for mining-induced microseismic data based on long short-term memory deep neural network," *Geomatics, Natural Hazards and Risk,* vol. 13, no. 1, pp. 908-933, 2022.

[57] P. Xie, J.-L. Boelle, and H. Puntous, "Generative adversarial network based fast noise removal on land seismic data," in *SEG International Exposition and Annual Meeting*, 2018: SEG, pp. SEG-2018-2995310.

[58] K. Jia and S. Zhou, "Machine learning applications in seismology," vol. 14, ed: MDPI, 2024, p. 7857.

[59] W. Zhu, K. S. Tai, S. M. Mousavi, P. Bailis, and G. C. Beroza, "An End-To-End Earthquake Detection Method for Joint Phase Picking and Association Using Deep Learning," *Journal of Geophysical Research: Solid Earth,* vol. 127, no. 3, p. e2021JB023283, 2022, doi: https://doi.org/10.1029/2021JB023283.

[60] J. Woollam *et al.*, "SeisBench—A toolbox for machine learning in seismology," *Seismological Society of America,* vol. 93, no. 3, pp. 1695-1709, 2022.

[61] Y. J. Tan *et al.*, "Machine-Learning-Based High-Resolution Earthquake Catalog Reveals How Complex Fault Structures Were Activated during the 2016–2017 Central Italy Sequence," *The Seismic Record,* vol. 1, no. 1, pp. 11-19, 2021, doi: 10.1785/0320210001.

[62] X. Wang *et al.*, "Small earthquakes can help predict large earthquakes: a machine learning perspective," *Applied Sciences,* vol. 13, no. 11, p. 6424, 2023.

[63] F. T. Johora, C. J. Hickey, and H. Yasarer, "Predicting geotechnical parameters from seismic wave velocity using artificial neural networks," *Applied Sciences,* vol. 12, no. 24, p. 12815, 2022.

[64] R. D. Esfahani, F. Cotton, M. Ohrnberger, and F. Scherbaum, "TFCGAN: Nonstationary ground-motion simulation in the time–frequency domain using conditional Generative Adversarial Network (CGAN) and phase retrieval methods," *Bulletin of the Seismological Society of America,* vol. 113, no. 1, pp. 453-467, 2023.

[65] M. Reichstein *et al.*, "Early warning of complex climate risk with integrated artificial intelligence," *Nature Communications,* vol. 16, no. 1, p. 2564, 2025.