



Computational intelligence approaches for seismic data analysis: a comprehensive analysis of detection and prediction methods

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सार— वैश्विक स्तर पर भूकंप की घटनाओं के लिए पूर्व चेतावनी जारी करना भूभौतिकीय समुदाय के समक्ष एक महत्वपूर्ण विषय है। तीव्र गति से विकसित हो रही प्रौद्योगिकी के कारण संगणनात्मक क्षमताओं में हुए हाल के विकास ने शोधकर्ताओं को एक नवीन दृष्टिकोण प्रदान किया है। इसके अंतर्गत नवीनतम प्रौद्योगिकियों का उपयोग करते हुए सांख्यिकीय प्रक्रियाओं को समेकित करने वाले उन्नत मॉडलों का निर्माण किया जा रहा है, ताकि भूकंपीय पूर्वसंकेतक गतिविधियों के संसूचन एवं पूर्वानुमान की जटिल चुनौती का समाधान किया जा सके। इस समीक्षा का उद्देश्य भूकंपीय आँकड़ों के विश्लेषण में संगणनात्मक बौद्धिकता (Computational Intelligence) के उपयोग से संबंधित उपलब्ध साहित्य का समेकित अध्ययन करना तथा एक विश्वसनीय केंद्रीकृत संदर्भ-संग्रह तैयार करना है, जो इस गतिशील क्षेत्र में कार्यरत शोधकर्ताओं एवं व्यावहारिक विशेषज्ञों के लिए उपयोगी हो सके। भूकंप के पूर्वानुमान की प्रभावशीलता निर्धारित करने हेतु विभिन्न सांख्यिकीय एवं संगणनात्मक आसूचना विधियों का उपयोग करने वाले पूर्ववर्ती अध्ययनों की समीक्षा के साथ-साथ, इस शोध-पत्र में विभिन्न पूर्वसंकेतक सूचकों तथा भूकंपीय-विद्युतचुंबकीय (seismo-electromagnetic) अनुसंधान के साथ उनके संबंधों का मूल्यांकन किया गया है। इससे वैज्ञानिक आधार, अंतर्निहित जटिलता तथा पद्धतिगत अस्पष्टता जैसे महत्वपूर्ण आयामों पर प्रकाश पड़ता है, जो संकेतों की विश्वसनीयता तथा बहुआयामी प्रतिरूप संसूचन को प्रभावित करते हैं। महत्वपूर्ण प्रगति के बावजूद अभी भी अनेक जटिल चुनौतियाँ विद्यमान हैं, विशेष रूप से पूर्वसंकेतकों के सटीक संसूचन एवं पूर्वानुमान के संबंध में, जो उन्नत सिग्नल-प्रोसेसिंग विधियों तथा बहुआयामी प्रतिरूप पहचान के लिए आवश्यक हैं। उन्नत विश्लेषणात्मक विधियों के उपयोग से संबंधित प्रमुख बाधाओं एवं संभावनाओं को रेखांकित करते हुए, अध्ययन इस क्षेत्र में अधिक सुदृढ़ एवं विश्वसनीय पूर्वानुमान क्षमता विकसित करने के लिए व्यापक हाइपरपैरामीटर खोज, गहन मॉडल सत्यापन तथा विभिन्न क्षेत्रों के बीच तुलनात्मक अध्ययनों की आवश्यकता की पुष्टि करता है।

ABSTRACT. It is not disputed that global need to early warn the occurrence of an earthquake is a key issue to the geophysical community. The recent changes in computational capabilities, brought about by the fast-paced technology, has presented a radical approach of researchers: the creation of advanced models that integrate statistical processes using the latest technologies in order to question the challenging undertaking of detecting and prognosticating precursory seismic activities. The objective of this review is to achieve a synthesis of the available literature on the use of computational intelligence in analyzing seismic data in order to formulate a credible centralized repository which can benefit scholars and practitioners working in this dynamic sector. In combination with a review of the prior research that used various statistical and computational intelligence procedures to determine the effectiveness of earthquake prediction, this paper evaluates a wide set of antecedent indicators and the relationship they have to seismo-electromagnetic research, thus shedding light on crucial dimensions that are worth further investigation, i.e., the scientific foundation, the intrinsic complexity, and the methodological ambiguity that dictate the integrity of signals and the multifaceted pattern detection. Though significant improvements have been made, there are still a number of thorny problems, especially in the accurate detection and prediction of prior signals, which is a prerequisite of the fine signal-processing methods, and the prerequisite of multi-dimensional pattern recognition. Having outlined the main obstacles and opportunities that the use of advanced analytical methods entails, the study confirms the need to respond to exhaustive hyperparameter searching, strict model validation,

and cross-regional comparative studies to take the field of study a step further in terms of more robust and reliable forecasting.

Key words– Earthquake precursors, Artificial Intelligence framework, Machine learning, Deep learning, Statistical analysis.

1. Introduction

Earthquake prediction remains one of the most challenging yet crucial fields of scientific research. With increasing global populations in seismically active zones, the timely accurate forecasting of seismic events has the potential to significantly enhance disaster response and mitigation efforts, thereby saving lives and minimizing infrastructure damage. Historical events, such as the 2011 Tohoku earthquake in Japan, impacted the socioeconomic toll, with damages more than hundreds of billions of dollars and thousands of lives lost, highlighting the gaps in current predictive capabilities. Despite decades of research, achieving precise long-term and short-term predictions remains challenging. Nonetheless, incremental progress through multidisciplinary investigations continues to refine our understanding, shifting focus from deterministic forecasts to probabilistic risk assessments and rapid detection systems.

Researchers have explored various methodologies for earthquake forecasting, focusing on identifying early signs or patterns in the earth's physical properties that may precede significant seismic activity.

The precursor approach involves studying unique earthquake specific signals or phenomena observed prior to earthquakes. Scientists work to find patterns or anomalies in the earth's crust, in seismic activity or other geophysical measurements that could serve as reliable precursors to earthquakes. These patterns can be discovered through both theoretical and computational/mathematical/statistical point of view.

In the past few decades cataloguing of earthquakes and analysis has improved measurements of earthquake magnitudes and frequencies. The moment magnitude scale (M_w), which is used widely today, gives a measure of the size of an earthquake. Unlike derived magnitude scales like the Richter scale (which determine magnitude from wave amplitude), it estimates released seismic energy, by calculating more than one seismic parameter. This offers a more accurate and consistent evaluation of the size of an earthquake, especially for larger occurrences.

Gutenberg's law, introduced by Gutenberg and Richter in 1956 (Gutenberg B *et al.*, 1956), is an empirical correlation that describes the relationship between earthquake magnitude (M) and the frequency of occurrence (F) within a specific region and time period. The law states

the frequency of earthquakes of a specific magnitude is inversely proportional to the magnitude itself. In other words, smaller earthquakes occur more frequently than larger ones. Gutenberg's law (equation 1) is often expressed in the form of a power law equation:

$$\log_{10}(F) = a - bM \quad (1)$$

where:

- (i) F represents the occurrence of earthquakes with a magnitude equal to or greater than M .
- (ii) a and b are constants specific to the region and time period under consideration.

This equation implies that for every unit increase in earthquake magnitude, the number of earthquakes decreases by a factor of 10. Therefore, larger earthquakes are less frequent compared to smaller ones.

Based on about 55 years (1970 to 2024) of historical data from the USGS and IMD earthquake catalogues, an average of 13,000 earthquakes with magnitudes between 4.0 and 4.9 occur each year. Notably, earthquakes occurring at depths between 0 and 30 kilometers can have a substantial impact. The earthquakes with a magnitude of 5.0 or above, recorded in the past several decades are shown in Table 1. It is observed that number of occurrences of earthquake is gradually increasing in each decade from 1970 onward except 1990-99.

It is worth mentioning that the scientific community is actively working on developing reliable earthquake early warning systems (EEWS) rather than precise earthquake prediction. EEWS aim to rapidly detect the initiation of an earthquake and provide warnings to regions that will be affected, allowing people to take immediate protective actions. These systems utilize real-time seismic data and advanced algorithms to estimate the magnitude and location of an earthquake as it unfolds, providing valuable seconds to minutes of warning time (Tehseen *et al.*, 2020).

This review synthesizes contemporary research on earthquake precursors, emphasizing data-driven analyses alongside statistical and computational methodologies for detection and forecasting. By examining these elements, the paper aims to highlight synergies that could bolster resilience against seismic risks, drawing on empirical evidence to guide future directions in this vital domain.

TABLE 1

Worldwide earthquakes with magnitude ≥ 5.0

Decades	The number of earthquakes within the magnitudes range between 5.0 to 9.0.				
	8.0 and above	7.0 to 7.9	6.0 to 6.9	5.0 to 5.9	Total in a decade (between 5.0 to 9.0)
1970-1979	6	118	954	11662	12740
1980-1989	4	106	1147	14,495	15752
1990-1999	6	148	1376	13,093	14623
2000-2009	13	130	1442	15,648	17233
2010-2020	11	149	1333	16797	18290
2021-2024 (December 31,2024)	3	56	471	6698	7228
Total (1970-December 31, 2024)	43	707	6723	78393	85866

TABLE 2

Satellites based sensors used to record ground, atmospheric and environmental parameters

Satellite Sensor	Parameters Recorded	Correlation with Earthquake Research and Prediction
GPS (Global Positioning System)	Ground deformation, plate movement	Monitoring tectonic plate motion, detecting crustal deformation before and after earthquake.
InSAR (Interferometric Synthetic Aperture Radar)	Ground deformation, surface displacement	Detecting and measuring surface displacement due to earthquakes, assessing fault behavior
GRACE (Gravity Recovery and Climate Experiment)	Changes in Earth's gravitational field (indicating mass redistribution)	Studying changes in groundwater, measuring crustal deformation, which can be associated with seismic activity
GOES (Geostationary Operational Environmental Satellite)	Weather patterns, cloud cover, atmospheric pressure	Monitoring atmospheric conditions, including atmospheric pressure changes, which can be related to earthquake precursor phenomena
GNSS (Global Navigation Satellite System)	Ground movement, tectonic plate motion	Detecting slow slip events along faults and monitoring strain buildup
MODIS (Moderate Resolution Imaging Spectroradiometer)	Land surface temperature, vegetation indices, aerosols, cloud properties, sea surface temperature	Monitoring changes in land surface temperature, vegetation health, and potential anomalies that could relate to stress on geological faults
AVHRR (Advanced Very High-Resolution Radiometer)	Sea surface temperature, vegetation indices, clouds, snow cover, aerosols	Climate monitoring, weather forecasting, oceanography, land cover analysis
SMAP (Soil Moisture Active Passive)	SMAP	Soil moisture content, which can be influenced by tectonic stress changes

TABLE 3

Earthquake precursors and observations

Sr. No	Precursor Type	Observation
1	Change in animal behaviours	Unusual animal behaviour observed preceding Haichang earthquake. Milk yield decrease observed 17-18 days before earthquake in Ibaraki Prefecture, Japan.
2	Temperature variation	Temperature rise ($\sim 10^{\circ}\text{C}$) observed prior to Lunglin earthquake and ($\sim 15^{\circ}\text{C}$) observed prior to Przhevalsk earthquake.
3	Hydro-chemical Precursors	Groundwater turbidity observed before and after Jabalpur earthquake. Chemical composition changes in groundwater documented before earthquakes in Tadzhik and Uzbekistan.
4	Water level change	Water level decrease observed 3-10 days before Lunglin earthquake, followed by rapid rise post-event.
5	Radon gas	Increase in radon gas levels in well water observed before Tashkent earthquake and at Kangra and Amritsar sites before Uttarkashi earthquake.
6	Oil wells	Increase in oil flow observed before significant earthquakes in Israel, northern Caucasus, and China.
7	Theory of seismic gap	Concept of seismicity gap discussed as an indicator of earthquake potential.
8	Changes in seismic wave velocity	Different waves (Primary-P, Secondary-S, Love- L) travel at varying velocities, providing lead time for earthquake detection.
9	Seismic electromagnetic field disturbance	ULF (Ultra Low Frequency) electromagnetic emissions and seismo-ionospheric disturbances observed before earthquakes.
10	Foreshocks	Increased seismic activity observed preceding Haichang earthquake, indicating foreshocks.

2. Data and methodology

2.1. Precursor analysis for seismic anomalies

Research on earthquake detection and prediction has been conducted for over a century. Early pioneers explored the possibility of developing an earthquake warning system that could provide advance notice, enabling measures like evacuation to be taken. However, Geller Robert (1997) argued that issuing reliable warnings for large earthquakes seemed to be probabilistic and effectively impossible. Although earthquakes are inherently unpredictable, certain indications can be analyzed.

Precursors are preliminary indicators of upcoming events, arising from a variety of geophysical shifts within the Earth's crust. The study of Lithosphere-Atmospheric-Ionospheric Coupling (LAIC) has investigated these changes (Pulinets *et al.*, 2011). It has been observed that earthquakes are associated with various physical and chemical changes, leading to the release of latent heat and alterations in the near-ground atmospheric field, including changes in air conductivity (Mahmood *et al.*, 2017; Pulinets *et al.*, 2004; 2011).

Recent developments in data collection through various satellites, monitoring networks, and computational

power have enabled more comprehensive analyses and improved understanding of seismic activity. Table 2 shows the various satellite sensors used to record the ground, atmospheric and environmental parameters.

In the context of earthquake prediction, a number of seismic indicators (Table 3) have been reported in literature (Bhardwaj *et al.* (2017), Hayakawa (2013), Hayakawa *et al.* (2016), Kalita *et al.* (2012), Katta *et al.* (2019), Kushwah *et al.* (2007), Pulinets *et al.* (2011), Virk *et al.* (2001)).

To enhance understanding, the following concise analysis categorizes these precursors mentioned in Table 3, linking observations to mechanisms and recent validations from reputed journals.

2.2. Biological and behavioral precursors

Changes in animal behavior, such as unusual activity before the Haicheng earthquake or milk yield drops 17-18 days prior in Japan, may reflect sensitivity to infrasound, vibrations, or gas releases (Hayakawa *et al.*, 2016). Recent studies suggest ties to electromagnetic or ionospheric shifts, with satellite-tracked animal movements showing anomalies days before events (Wikelski *et al.*, 2020).

2.3. Thermal and atmospheric precursors

Temperature variations (~10-15°C rises) precede events like Lunglin and Przhevalsk, linked to fault friction or radon-induced heating under LAIC models (Bhardwaj *et al.*, 2017). Modern satellite analyses (e.g., MODIS) confirm anomalies 1-30 days in advance, isolated via ML from non-seismic noise (Sun *et al.*, 2022).

2.4. Geochemical and hydrological precursors

Hydro-chemical shifts, including groundwater turbidity in Jabalpur or ion changes in Tadjik/Uzbekistan, arise from fracture-induced aquifer mixing (Virk *et al.*, 2001). Water level drops (3-10 days pre-Lunglin) and radon spikes (Tashkent/Uttarkashi) signal permeability increases (Kushwah *et al.*, 2007; Katta *et al.*, 2019). Oil flow surges in Israel/Caucasus/China indicate fluid dynamics. Continuous monitoring correlates radon with M>5 quakes at 80% accuracy in fault zones (Radon Anomalies and Earthquake Prediction, 2025).

2.5. Seismological and geophysical precursors

Seismic gaps highlight strain-prone quiet zones. Wave velocity changes (P, S, Love waves) provide detection lead time via stress-altered rock properties (Hayakawa, 2013). Electromagnetic disturbances (ULF emissions, ionospheric perturbations) stem from piezo-effects (Pulinets *et al.*, 2011; Kalita *et al.*, 2012). Foreshocks, as in Haicheng, indicate accelerating slip. These precursors underscore LAIC interconnections, with multi-parameter AI approaches reducing false positives for early warnings.

3. Results and discussion

3.1. Detection and prediction of seismic anomalies

Scientific and academic researchers are increasingly focusing on short-term earthquake prediction using various precursors and data analysis techniques. Due to Availability of various environment indicators through various satellites and emerging technologies in integration with statistical analysis and computational intelligence techniques are employed for detecting precursory signatures. Table 4 illustrate the decade wise advancement in precursor-based research.

There are a vast literature and active research being conducted worldwide for earthquake prediction (Fister *et al.*, 2014). Numerous algorithms and techniques have been proposed by utilizing data collected from the aforementioned sensors. Seismic waves originating from the interior of the Earth propagate to the surface, causing earthquakes. Efficient earthquake prediction often relies on

feature extraction from seismic signals. Various algorithms, such as the M8 algorithm for intermediate-term earthquake prediction and EEW (Earthquake Early Warning) algorithms, have been proposed (Narsimha *et al.*, 2013). However, these methods have several limitations: the M8 algorithm's performance is constrained by data accuracy and heterogeneity, limited statistical significance in retrospective tests (with only 6 out of 10 target earthquakes predicted in forward simulations at low confidence levels), and potential failure to predict certain large events due to insufficient precursory seismicity patterns; meanwhile, EEW algorithms face trade-offs between alert speed and accuracy, magnitude saturation for events above M7, challenges in distinguishing aftershocks or swarms (leading to over estimation of intensity and false alarms), and difficulties capturing finite fault ruptures in large earthquakes. These issues can result in false alarms or missed predictions. To address the challenges of seismic data analysis, statistical and artificial intelligence (AI) techniques have been employed in previous studies.

Statistical techniques such as Poisson models, stochastic models (Kagan *et al.*, 1987), Fast Fourier Transform (FFT), wavelet analysis (Prasad *et al.*, 2014; Sahana, 2014; Raju *et al.*, 2015) are used for earthquake detection.

AI based artificial neural network models and their variations (Suratgar *et al.*, 2008; Moustra *et al.*, 2011; Alarifi *et al.*, 2012; Reyes *et al.*, 2013; Florido *et al.*, 2016; Morales *et al.*, 2016; Asim *et al.*, 2018), fuzzy techniques, machine learning (Nirmala *et al.*, 2016; Asim *et al.*, 2021; Johnson *et al.*, 2021), deep learning (Vardaan *et al.*, 2019; Bao *et al.*, 2021; Xiong *et al.*, 2021; Yousefzadeh, *et al.*, 2021), hybrid computation, evolutionary techniques and data mining (Ikram *et al.*, 2015; Nivedhitha and Krishna, 2016) applied in the field of earthquake detection and prediction.

Data mining techniques are providing new and in-depth insights. Data scientists are optimistic about applying these techniques in this promising area of research. Unsupervised clustering algorithms and association rule mining have been applied to historical earthquake data for prediction purposes (Ahmad *et al.*, 2019; Samadi *et al.*, 2020). Katta *et al.* (2025) have applied hierarchical K-means clustering for an in-depth analysis of the highly seismic zone in Gujarat, India.

3.2. Statistical analysis approaches

Statistical methods are providing high-quality structures of the pattern finding, measuring an uncertainty and enhancing a prediction power. These methods are useful in the treatment of vast amounts of geophysical,

TABLE 4

Timeline based precursory research

Sr. No	Time Scale	Precursor Research
1	During 1980s	Research primarily focused on examining seismological parameters and making observations related to geoelectrical and geohydrological aspects, such as water level changes, electric charges, self-potential, and similar measurements.
2	During 1990s	Geomagnetic, geoelectric field data collected from Digital seismograph-based observatory system at strategic locations along with geochemical precursors.
3	During 2000s	Analysis of GPS satellite data is used to study the patterns of crustal deformation before and during earthquakes, ULF (Ultra-low frequency)/VLF (Very low frequency) emissions, the detection of thermal anomalies using satellite technology, and methods to predict earthquake nucleation.
4	Recent development	Multi parametrized optimization techniques (Soft computing and hybrid computing), Development of Python based systems for forecasting.

TABLE 5

Statistical approaches used in earthquake research

Sr. No	Authors	Year	Area of research	Methodology	Results
1	Zorkun et al.	2025	Ionospheric disturbances prior to large earthquakes	Random Forest classification, 5-fold cross-validation, extraction of statistical features (e.g., mean, variance, skewness) from TEC data.	High accuracy (93-98%) in distinguishing seismic precursors from geomagnetic disturbances; correlation with earthquake magnitude observed.
2	Chetia et al.	2025	TEC anomalies as precursors in Northeast India	Probability analysis, multiple linear regression on TEC and environmental factors	80% earthquake likelihood for prolonged TEC anomalies; low R^2 indicates need to control for solar and geomagnetic influences
3	Friedrich et al.	2025	Multiscale seismic precursors before major earthquakes	Natural Time analysis, Method of Critical Fluctuations-Based approach.	Identification of criticality in seismicity patterns, interpreting failures as phase transitions for prediction
4	Rasheed et al.	2025	Size estimation of precursor manifestation zones	Small perturbation methods, numerical computations, quantitative analysis of LCAI coupling	Modified disturbance radius equations for lithosphere, atmosphere, and ionosphere; validated with global earthquake cases.
5	Keskin, S et al.	2023	Predict hazards by examining anomalies before earthquakes	Examined mathematical and statistical relationships between soil radon gas (Rn-222) and earthquakes, as well as atmospheric total electron content (TEC) by ARIMA (Autoregressive Integrated Moving Average) simulation model	Relationship found between soil radon gas and micro-seismic activity; TEC increases with relative Rn gas concentration before main shocks; ARIMA model predicts future Rn concentrations
6	Zhang et al.	2022	Probabilistic Seismic Hazard Assessment	Analysis of earthquake catalogue homogeneity for Probabilistic Seismic Hazard Analysis (PSHA)	Homogeneous earthquake catalogues crucial for accurate PSHA modelling.
7	Hayakawa et al.	2022	Seismogenic lithospheric radiation analysis	Polarization ratio, wavelet analysis, Schumann resonance	Positive connection between methods and detection of seismogenic emissions.
8	Nina et al.	2022	Variations in VLF (very low frequency) signal during seismic activity	Analysis of VLF signal noise amplitude during seismic activity in Central Italy	Reduction in noise amplitude observed preceding strong earthquakes. Variations start up to two weeks before seismic activity.
9	Marchetti et al.	2022	Investigation of lithosphere-atmosphere ionosphere interactions preceding the eruption of La Palma Cumbre Vieja Volcano	Analysis of seismic activity, atmospheric alterations, magnetic field, ionosphere using ground and space-based systems	Temporal migration of seismicity observed preceding eruption. Anomalies in various parameters detected months before eruption.

TABLE 5 Continued

10	Sekertekin, A. et al.	2020	Examine the pattern of potential earthquake precursors before and after the 2013 Mw 7.7 Awaran earthquake	Analysed TEC values and LST (Land Surface Temperature) and aerosol values from MODIS using moving median and 2σ interval methods to detect anomalies	Identified TEC anomalies 3 and 5 days before the earthquake; observed systematic LST and AOD (Aerosol Optical Depth) changes; highlighted TEC, LST, and AOD as important precursors, requiring further method and data development.
11	Mukhopadhyay et al.	2020	Analysis of thermal anomaly data preceding earthquakes	Analysis of satellite-derived thermal anomaly data for earthquake prediction	Utilization of RETIRA index for analysing thermal anomaly data preceding earthquakes, contributing to earthquake prediction research.
12	Katta et al.	2019	Review of early earthquake signs	Analysis of environmental conditions, ground movements, Earth's crust structure	Seismogenic ULF (Ultra Low Frequency) emissions, DEMETER satellite data, TEC anomalies, ionospheric disturbances, bio-electric amplitude used as pre-seismic indicators.
13	González et al.	2019	Novel method for earthquake magnitude prediction	Proposal of a novel earthquake magnitude prediction method	Proposal of a novel method for earthquake magnitude prediction.
14	Xie et al.	2019	Evaluation of earthquake catalogue completeness and 'b-value' determination	MAXC technique, bootstrap approach for earthquake catalogue completeness and b value determination	Decreasing trend in b value observed prior to significant earthquakes, with statistical significance.
15	Chelidze et al.	2018	Complexity of seismic time series: measurement and application	Dynamical systems, seismicity. Investigation of long-term correlations in seismic data.	Identification of power law behaviour and hidden non-linear structures in seismic distributions.
16	Bhardwaj et al.	2017	Impact of land surface temperature (LST) changes on earthquake prediction	Analysis of land surface temperature changes before earthquakes	Unusual changes in land surface temperature observed before earthquakes occur.
17	Zhang et al.	2013	Study of changes in surface latent heat flux (SLHF) connected to marine earthquakes	Examination of daily SLHF data for marine earthquakes	Precursory SLHF variations before certain earthquakes tend to have low amplitudes, making them challenging to identify as anomalies.
18	Kalita et al.	2012	Prediction of earthquakes using total electron content (TEC) data	Peak detection algorithm, automated template matching approach, artificial neural network for earthquake prediction	Methodology for earthquake prediction using GPS-generated TEC data proposed.
19	Pulinets et al.	2011	Exploration of short-term earthquake indicators in the atmosphere, atmospheric electricity, ionosphere, and magnetosphere	Multidisciplinary approach, Lithosphere-Atmosphere-Ionosphere Coupling model, Interdisciplinary Space-Terrestrial Framework	Unified theory systematically confirming different signs of earthquakes proposed.
20	Singh et al.	2010	Analysis of surface air temperature and atmospheric variables at the epicentre of the Haiti earthquake	Examination of surface air temperature and atmospheric variables at the epicentre of the Haiti earthquake	Significant changes observed in surface and atmospheric variables before the Haiti earthquake.
21	Kushwah et al.	2007	Prediction of seismic activity signals using null hypothesis	Long-term ultra-low frequency (ULF) data analysis techniques	Various studies predict seismic activity signals using null hypothesis.
22	Schekotov et al.	2007	Correlation between seismic activity and local changes in the magnetic field	Observation of seismic ULF/ extremely low frequency (ELF) emissions, statistical analysis	Broad emission in ULF/ELF frequency range observed before earthquakes, with unique features.

atmospheric and ionospheric data. It allows researchers to identify minute abnormalities that can be an indication of imminent earthquakes. Table 5 presents the newest

analytical methods used by scientists to clarify the intervalidities of seismic. Examples include time series based models such as ARIMA which are used to predict

precursor concentrations whereas probabilistic schemes are employed to determine the hazard risks by guaranteeing catalogue homogeneity. Further, technologies include the use of anomaly detection by wavelet analysis or polarization ratios to map seismogenic emissions to measurable changes. Kayal *et al.* (1991) indicated that to a certain degree multi-precursory analysis is able to reduce the uncertainties by integrating the various datasets, which has been modified with the modern computational tools.

In order to enhance the predictive powers, new research has focused on combining machine learning with conventional statistical techniques that would enable enhanced differentiation between seismic precursors and other environmental disruptions. To illustrate, in a paper concerned with pre-major earthquake ionospheric disturbance, the authors used the Total Electron Content (TEC) data analysis with the help of the Random Forest classification algorithm and 5-fold cross-validation. The model demonstrated high accuracy (93-98%) in detecting pre earthquake anomalies three days beforehand with statistical features of mean, variance, skewness, and kurtosis extracted, which are beyond the capabilities of TEC estimates, and demonstrates the potential of early warning systems (Zorkun *et al.*, 2025).

Probability analysis and multiple linear regression have also been used to correlate TEC anomaly with earthquake parameters in the Eastern Himalaya region. This type of strategy found out that the probability of seismic activity of finding TEC derivations beyond 2-sigma in more than 16 days was 80 percent (Chetiya *et al.*, 2025). The other side of innovations is the multiscale study of the predecessors of failures, which is premised on statistical physics. The Method of Critical Fluctuations-Based approach and Natural Time analysis aided the researchers in studying the patterns of seismicity associated with the 2023 Mw 7.7 Turkey earthquake (Friedrich *et al.*, 2025). In addition, quantitative Lithosphere – Coversphere – Atmosphere-Ionosphere coupling analysis as well as small perturbation has also been used in trying to optimize the modeling of precursor manifestation zones. This has led to new disturbance radius equations that have been experimented all over the world on earthquakes, and it is more accurate in the representation of atmospheric and ionospheric viscoelastic properties (Rasheed *et al.*, 2025). The developments mentioned above explain the need to combine statistical rigor and multidisciplinary data to render earthquake forecasting models more credible.

3.3. Artificial intelligence for earthquake detection and forecast

Artificial intelligence (AI) surpassing humans in prominence as a result of its improving efficacy in a variety

of areas, including sensory processing and complex reasoning. Its stoicism excels in all significant decision-making components. Because they are less visible than they are in other machine learning and deep learning projects, "hidden variables" in earthquake forecasting are challenging for AI to recognize.

3.3.1. AI framework and techniques for seismic data analysis

The analysis and processing of seismic data have become more accurate, efficient, and automated with the introduction of artificial intelligence (AI) based Machine Learning (ML) and Deep learning (DL). Owing to the growing application of AI in seismological-related applications such as seismic event detection, earthquake early warning (EEW), and earthquake prediction, there have been significant advances in earthquake monitoring, hazard assessment, and risk mitigation. Among the key applications of AI in seismology, the identification of seismic events is one of them, and the frameworks of the analysis of seismic data that have been modified to include the necessary precursors are proposed by Banna *et al.* (2020). Restructured to include the identification of important precursors, the framework of seismic data analysis has been offered based on a literature review of different AI approaches that have been suggested to analyze seismic data. The proposed framework is shown in Fig. 1.

The AI framework for seismic data analysis involves techniques for interpreting and extracting valuable insights from seismic signals. This framework includes several steps that enable the processing, understanding, data extraction and classification of seismic events for detection and prediction.

Overall, the AI framework for seismic data analysis provides a structured approach to leveraging the power of artificial intelligence in understanding and interpreting seismic signals, enabling more efficient and accurate analysis of seismic events for various applications, including earthquake monitoring, hazard assessment, and resource exploration. Choosing the best method for the given problem enables achieving a higher level of efficiency. The hyperparameter adjustment, makes the algorithm more data-driven and helps avoid overfitting. Therefore, being able to forecast earthquakes and identify correlations between them would help us better comprehend this phenomenon and, ultimately, save human lives. Table 6 shows the recent AI-based approaches followed to detect and predict earthquakes in most active earthquake prone areas. Neural Network based algorithms were the first choice of researchers on various precursors.

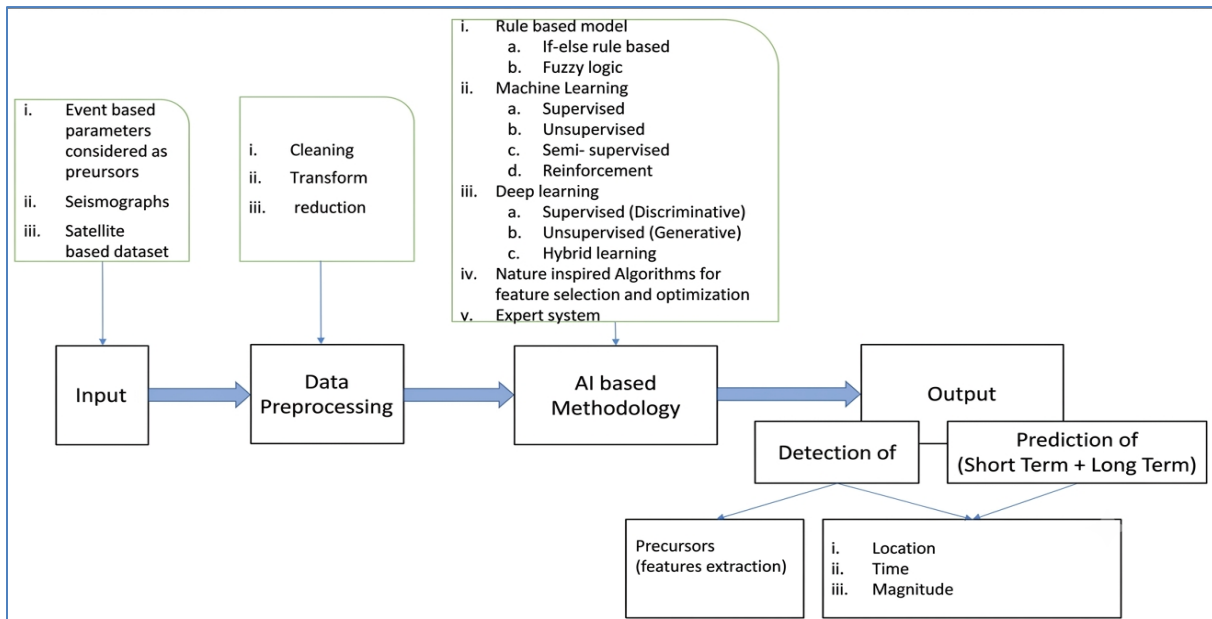


Fig. 1. AI framework for seismic data analysis

TABLE 6

Worldwide earthquake prone zones and associated machine learning algorithms used for seismic data analysis and processing

Sr. No.	Zone	Algorithms used
1.	South California (USA)	LM-BP (Levenberg Marquardt Back Propagation), RBF (Radial Basis Functions)
2.	Yunnan (China), Northeast India, North California (USA), Iberian Peninsula, Chile, Alaska (USA)	BPNN (Back Propagation Neural Network (BPNN))
3.	Northern Red Sea	Statistical predictors with SVM (Support Vector Machine, NB (Naive Bayes)
4.	Chile	M5P (Binary regression tree model based on Quinln's M5 model), NB, SVM
5.	Iberian Peninsula	SVM, NB
6.	Southwest China	KNN (K-Nearest Neighbour), SVM, NB, J48
7.	Tokyo (Japan)	BPNN, PSO-BPNN (Particle swarm optimization-BPNN)
8.	China	Random Forest, LPBoost ensemble
9.	Hindukush (Pakistan)	Linear Programming Boost (LPBoost), Recurrent Neural Network (RNN), random forest

Among the prominent data mining techniques utilized in earthquake prediction, neural networks, the Bayesian belief network, decision trees and Support vector machine stand out as primary solutions to the inherent challenges associated with forecasting earthquakes, tsunamis, landslides, and other micro-seismic activities.

Artificial neural networks (ANN), support vector machines (SVM), and decision trees have gained significant popularity as data mining models in earthquake prediction research. Various ANN models have been extensively employed for prediction purposes, and their

performance has been evaluated using seismometer data. Evolutionary techniques, including genetic algorithms (GA) and particle swarm optimization (PSO), have also found applications in this domain (Table 7).

However, it has been observed that the majority of research endeavors tend to focus on utilizing independent techniques and relying on a singular type of precursor specific to a particular region or individual earthquake. The multiparameter based techniques can explore the details of seismic events and its impact on environments.

TABLE 7

Emerging techniques used in earthquake detection and prediction

Sr. No	Authors	Area of research	Methodology	AI/ML/DL techniques	Results
1	Katta, V.S. et al (2025)	Seismic analysis in Gujarat, India	Multi-level clustering to identify seismic trends.	K-Means clustering	Distinct seismic clusters offer insights into seismic activity patterns and geological correlations
2	Akhoondzadeh, M. et al.(2023)	Investigate lithosphere–atmosphere–ionosphere (LAI) anomalies for earthquake prediction	Analysis of 52 time series over six months using satellite data (Swarm constellation), Google Earth Engine (GEE), Giovanni data service, and USGS earthquake catalogue	Mamdani fuzzy inference system (FIS)	Number of seismic anomalies increased ~33 days before the earthquake, peaking one day prior; highlights the potential for developing early warning systems based on geophysical data.
3	Draz, M. U. et al (2023)	Detection of ionosphere and atmosphere precursors related to earthquakes using GNSS and remote sensing data	Analyzed multiple atmospheric and ionospheric parameters (Sea Surface Temperature, Air Temperature, Relative Humidity, Outgoing Longwave Radiation, TEC) before and after the February 13, 2021, Mw 7.1 earthquake in Japan. Employed standard deviation, wavelet transformation, NARX model, and LSTM (Long Short-Term Memory) network to identify anomalies.	Standard Deviation (STDEV), Wavelet Transformation, NARX, LSTM	Anomalous variations in atmospheric and ionospheric precursors were detected before and after the earthquake. Unusual variations in atmospheric constituents occurred 6 and 5 days before the main shock. Both statistical and machine learning methods confirmed these anomalies, supporting the LAIC mechanism. Further techniques are needed to improve forecasting capabilities.
4	Fox, G. C. et al. (2022)	Review and introduce new approaches for nowcasting earthquakes using deep learning	Analyzed earthquake data for Southern California (1950-2020) using recurrent neural networks (RNNs) and transformers; measured quality using Nash Sutcliffe efficiency.	Recurrent Neural Networks (RNNs), Transformers	Achieved promising initial results in predicting earthquake activity using RNN and transformers, with evaluation based on Nash Sutcliffe efficiency metric; identified the need for further exploration of hyperparameters, validation techniques, and model comparisons across different regions..
5	Sun et al. (2022)	AI applications in Earth sciences	Overview of AI applications, challenges, and opportunities in Earth sciences.	AI overview	Comprehensive examination of AI's role in Earth sciences, providing a clear trajectory for future development.
6	Mukherjee et al. (2022)	Ensemble Earthquake Prediction Method (EPPM)	Utilization of EPPM to enhance earthquake forecasting accuracy.	Ensemble learning	Superior performance of EPPM in earthquake prediction compared to individual ML techniques, with enhanced prediction capabilities and resilience.
7	Chelidze et al. (2022)	Machine learning-based forecasting of earthquakes	Training machine learning model on imbalanced dataset for earthquake forecasting.	Machine learning	Identification of effective metric Matthews' correlation coefficient (MCC) for earthquake probability forecasting, highlighting challenges of imbalanced data and forecasting model efficiency.

TABLE 7 Continued

8	Yuan et al. (2021)	Enhancement of K-means clustering for earthquakes	Incorporation of earthquake distance in K-means clustering.	Machine learning	Improved earthquake clustering based on space-time-magnitude distance, with evaluation using SSE, DBI, CH index, and silhouette coefficient.
9	Rini et al. (2021)	Spherical K-means clustering for earthquake events	Application of spherical K-means clustering on earthquake data.	Machine learning	Identification of earthquake clusters using spherical clustering method based on directionality of seismic events.
10	Bao et al. (2021)	CNN-based earthquake magnitude classification	Development of CNN-based approach for earthquake magnitude classification.	Deep learning (CNN)	Effective earthquake magnitude classification using 3D feature map and SMOTE oversampling to address data imbalance.
11	Yousefzadeh et al. (2021)	Investigate the effect of spatial parameters on ML algorithms' performance for predicting earthquake magnitudes in Iran	Investigation of spatial characteristics' influence on machine learning algorithms for earthquake prediction. Compared performance of SVM, Decision Tree (DT), Shallow Neural Network (SNN), and Deep Neural Network (DNN) using a new parameter, Fault Density (FD), along with conventional seismic parameters	Machine learning (SVM, DT, SNN, DNN)	Evaluation of SVM, DT, SNN, and DNN models in earthquake prediction, introducing fault density parameter for improved performance.
12	Jain, R et al (2021)	Develop an earthquake prediction model based on position and depth using ML and DL algorithms	Used Random Forest (RF) Regression, Multi-Layer Perceptron (MLP) Regression, and Support Vector Regression (SVR) on a processed dataset from the USGS; evaluated models with Root Mean Square Error (RMSE)	Random Forest Regression (RF), Multi-Layer Perceptron (MLP) Regression, Support Vector Regression (SVR)	MLP Regressor outperformed RF and SVR with the lowest RMSE values, demonstrating better accuracy in predicting earthquakes based on position and depth. Exploratory data analysis was also conducted.
13	Brykov, M. N., et al. (2020)	Develop machine learning models to predict earthquakes using a dataset from the LANL earthquake prediction competition	Used XGBoost algorithm with 6-fold cross-validation; employed backward feature elimination and forward feature construction to optimize features	XGBoost	Best subset of 10 features yielded a mean absolute error (MAE) of 1.913 s; identified important statistical characteristics and autocorrelation features for effective earthquake prediction. Highlighted the importance of periodic acoustic data spikes as precursors.
14	Ahmad et al. (2020)	Fuzzy K-Means Clustering for earthquake event analysis	Application of Fuzzy K-Means Clustering for earthquake event clustering based on depth.	Machine learning (clustering)	Identification of deep and shallow earthquake clusters in Indonesia, providing insights into seismic activity distribution.
15	Samadi et al. (2020)	KNNS-based earthquake clustering	Development of KNNS-based method for earthquake clustering.	Machine learning (KNNS)	Improvement of mechanism identification and pattern recognition of active seismicity through accurate earthquake clustering.

TABLE 7 Continued

16	Gitis, V. G. et al.(2019)	Develop two machine learning methods for seismic hazard forecasting	Method 1: Approximation of interval expert estimates using regression for spatial forecasting of Mmax; Method 2: Minimum area of alarm for spatio-temporal forecasting of strong earthquakes using retrospective data	Regression (Method 1), Retrospective data analysis (Method 2)	Method 1 effectively formalized expert knowledge to forecast Mmax spatially; Method 2 identified alarm areas for target earthquakes, forming the basis of an automatic forecasting platform with satisfactory results in the Mediterranean and Californian regions.
17	Ahmad et al. (2019)	Parallel processing for earthquake data analysis	Utilization of parallel processing in Hadoop for earthquake data mining and analysis.	Parallel processing	Investigation of Pig-Hive optimization, MapReduce, and Impala frameworks for earthquake data processing and ensemble algorithms for prediction.
18	Vardaan et al. (2019)	LSTM for earthquake forecasting	Utilizes Long Short-Term Memory (LSTM) and Feed Forward Neural Network (FFNN) to model and predict earthquake sequences. The performance of LSTM is compared to that of FFNN.	Deep learning (LSTM)	LSTM model demonstrated superior performance over FFNN in predicting earthquake magnitude, depth, time, latitude, and longitude. LSTM achieved an R ² score 59% higher than FFNN, indicating better trend capture in earthquake data. Future improvements suggested combining different deep learning models for real-time applications.
19	Asim et al. (2018)	Seismic event prediction using machine learning	Development of SVR-HNN system for seismic event prediction.	Machine learning (SVR, HNN)	Utilization of mRMR feature extraction and EPSO weight optimization for seismic event prediction in various regions.
20	Novianti et al. (2017)	K-means clustering for epicenter analysis	Utilization of K-means clustering for analyzing earthquake epicenter clustering.	Machine learning (clustering)	Identification of earthquake clusters in Bengkulu Province, providing insights into seismic activity patterns.
21	Kanarachos, S et al (2017)	Anomaly detection in time series data for applications like earthquake prediction, intelligent transportation, and structural health monitoring	Combines wavelets, neural networks, and Hilbert transform for robust anomaly detection. Uses probabilistic Receiver Operating Characteristics (ROC) for determining anomaly detection threshold and statistical significance.	Neural Networks, Wavelet Analysis, Hilbert Transform	Developed a unique deep neural network structure that reconstructs normal behavior. Demonstrated that the method could automatically detect anomalies in seismic electrical signals for earthquake prediction. Highlights that the method is adaptable and facilitates online learning. Compared favorably with other road anomaly detection methods.
22	Narayana Kumar et al. (2016)	BPNN for earthquake tremor anticipation	Utilization of BPNN for anticipating earthquake tremors in Himalayan belt district.	Machine learning (BPNN)	Transformation of seismic field data into seismicity markers for better understanding and prediction of earthquake magnitudes.

3.4. Challenges in AI Techniques for Earthquake Prediction

3.4.1. Hyperparameters Tuning & Optimization

One of the significant challenges in applying machine learning (ML) and deep learning (DL) techniques to earthquake prediction lies in the optimization of hyperparameters. Hyperparameters, which govern the training process and model architecture, play a crucial role in determining the performance and accuracy of predictive models.

Finding the optimal set of hyperparameters can be a complex and time-consuming process, often involving extensive experimentation and computational resources. The need for effective hyperparameter tuning is imperative, as suboptimal configurations can lead to underfitting or overfitting, ultimately affecting the reliability of earthquake predictions. Therefore, advancing methodologies such as automated hyperparameter optimization and adaptive learning techniques are essential for improving model performance and ensuring robust predictive capabilities.

Computational needs of hyperparameter optimization have been under the light recently due to challenges in executing hyperparameter optimization with dealing geotechnical problems such as the process of liquefaction of soil during earthquakes. As an example, fox and Bayesian optimization have been suggested to predict the factor of safety against liquefaction using hyperparameterized artificial neural network architectures that rely on random search, grid search, or Bayesian optimization. Models without such tuning are poorly performing, and these root-mean-square error reductions can be obtained by optimization, showing how hard it is to obtain accurate predictions in sparse seismic data (Kurnaz *et al.*, 2023). Equally, in the construction of the hybrid Long Short-Term Memory (LSTM) models in magnitude prediction of seismically active regions such as Turkey, control mechanisms such as Genetic Algorithms, Particle Swarm Optimization, Grid Search, and Random Search have been used to optimize parameters of the models, including the number of units and the number of epochs. The approaches are used to overcome the irregularity of the inefficiency of traditional trial-and-error methods, which are computationally-intensive and not over fractured by time-series forecasting (Akın *et al.*, 2026). The other method is the hybrid stacked ensemble models to assess the damage in the aftermath of earthquakes, whereby the tuning aspect is based on the base learners such as Balanced Random Forest and XGBoost to incorporate the unbalanced data (caused by real events) like the 2023 Kahramanmaraas earthquakes. This highlights how it

is hard to optimize to detect minority classes in seismic environments, in which the untuned models do not model the case (Mostofi *et al.*, 2025). The cited cases demonstrate the necessity of effective and automated tuning strategies to effectively defeat resource-consuming processes and increase model resilience to earthquake-related tasks.

3.4.2. Validation methods and model reliability

The other important issue with the implementation of AI/ML methods in earthquake prediction is model validation. Predictive models must be rigorously validated so that they can be used on data that has not been observed as well as not just overfitted to historical data. Conventional validation techniques, including cross-validation, might not be adequate under the circumstances that seismic data is unique, and it may be sparse and extremely variable. This is in urgent need of the development and refinement of validation methods, which consider the complex time and space-dependent properties of seismic events. This involves integrating domain knowledge validation strategies, e.g. event-based validation and incorporation of real-time data streams to dynamically evaluate model performance. It is important to ensure that models are accurate and reliable in various scenarios to ensure that they can be used in the early warning systems. In order to address these issues, studies have focused on the well-developed validation systems which are seismic vulnerability specific. As an example, when it comes to assessing the masonry buildings after the occurrence of such events like the L'Aquila earthquake in 2009 and the earthquake in Central Italy of 2016-2017, the machine learning models were trained on the data related to structures and tested on multiple case studies to check the generalizability. This involved plotting the parameters of vulnerability along with the process of damage and data on in-situ surveys that demonstrated troubles in obtaining comparable data sets to compare events and offer a robust model (Pinasco *et al.*, 2025).

The ensemble ML models to forecast seismic needs on the structures like special concentrically braced frame have made use of meta-models like XGBoost on the hold-out predictions of the base learners and have achieved large coefficients of determination ($R^2 > 0.90$) by testing the model on diverse measures of intensity. The challenge is that non-stationary properties of ground motion, should be considered due to the fact that in the classical methods the importance of time-frequency domain characteristics is underestimated, which delivers less valid predictions with a limited size of the dataset (Wasse *et al.*, 2024). Moreover, the comparative studies of the ML and DL algorithm to forecast earthquakes employ the use of point-based

ranking, which is founded on popularity and accuracy, which are grounded on thousand research studies. These highlight the difficulties of validation including the variability and interpretability of data and hence the need to have scalable models that are consistent in the accuracy of different seismic records. Such efforts elaborate on the necessity of having an interdisciplinary authentication to minimize overfitting in order to foster trust in AI-based early warning systems (Moghadamnejad *et al.*, 2026).

3.4.3. Cross-regional model comparisons

Another important issue of concern is the generalizability of earthquake prediction models in various geographical locations. The geological and environmental characteristics of the regions can affect the seismic activity and thus possibly impair the predictive model performance. It then becomes essential that the models formulated in the specific areas must undergo cross-regional tests so as to estimate to what extent a model which is constructed based on information on a given area can be applied to other situations with different seismic characteristics. These comparative analyses include the comparisons of models on a wide range of regional data and the mitigation of data heterogeneity and regional biases. The exploitation of adaptive type of models that can be used to fit the regional peculiarities and, therefore, their increased generalizability in a range of seismic regions, is one fertile avenue in the further development of earthquake forecasting research. This could be achieved by comparative projects, such as joint work and building joint data sets of research communities, and eventually create more broadly generalizable prediction systems.

4. Conclusions

This review paper delves into the significant strides made in the field of seismology through the application of statistical and emerging techniques. The findings underscore the profound impact of these approaches, particularly in earthquake detection and cataloging, yielding remarkable improvements in the comprehensiveness of seismic event records. With the unprecedented spatiotemporal resolution, deep-learning techniques have demonstrated remarkable performance across diverse local environments, paving the way for more accurate and thorough earthquake catalogs.

Furthermore, the study elucidates the far-reaching implications of more comprehensive earthquake catalogs. By harnessing the power of these enriched datasets, advancements in both statistical and physics-based forecasting, as well as artificial intelligence-based

methodologies, become attainable. The potential for more accurate predictions and a deeper understanding of seismic phenomena emerges as a promising avenue for future research and practical application. Amid the landscape of modern seismology, where machine learning applications have seen a surge in data processing tasks, a noticeable trend towards addressing inverse problems is emerging. Inverse problems focused on deducing the underlying causes and parameters of seismic events from observed data, signifies a shift towards more sophisticated and nuanced analyses.

Moreover, the research anticipates a forthcoming role for unsupervised machine learning approaches. These methods, encompassing techniques like clustering and dimensionality reduction, offer an innovative means to glean insights from complex, high-dimensional seismic datasets without the constraints of labeled training data. This projection speaks to the evolving nature of seismic data analysis, driven by the potential of unsupervised exploration.

In essence, this review encapsulates the advancing role of deep learning (LSTM, CNN) and machine learning techniques particularly back propagation neural network, SVM, naïve bayes, in reshaping various facets of seismology. From the foundational tasks of earthquake detection and cataloging to the intricate realms of forecasting and exploratory data analysis, these methodologies hold transformative potential. By seamlessly integrating these approaches, a richer comprehension of seismic events and their far-reaching impacts is within reach. As the seismic landscape evolves, the synergy between artificial intelligence and seismology promises to unravel new insights and reshape our understanding of the Earth's dynamic processes.

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

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