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Artificial intelligence based real-time earthquake prediction

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ABSTRACT

Earthquake prediction is considered a vital endeavour for human safety. Effective earthquake prediction can drastically reduce human damage, which is of utmost importance to the community and individuals. In the current research world, there is a boom in scientific interest in the prediction of seismic events. With the technological revolution in data acquisition, communication networks, edge–cloud computing, the Internet of Things (IoT), and big data analysis, it is feasible to develop an intelligent earthquake prediction model for early warnings at vulnerable locations. Conspicuously, a collaborative IoT–Edge-centered smart earthquake monitoring and prediction framework using cloud and edge computing are proposed. IoT technology is utilized to acquire real-time sensor data, which is forwarded to the edge layer for feature classification utilizing a novel bayesian belief model technique. Furthermore, Adaptive Neuro-Fuzzy Inference System (ANFIS) mechanism is employed to forecast the magnitude of earthquakes in the cloud layer. Based on the experimental simulation, enhanced effectiveness is acquired for the presented framework in terms of classification performance (Precision (92.52%), Sensitivity (91.72%), and Specificity (91.01%)). Additionally, results show that the utilization of edge computing significantly reduces computational delay (23.06s). Moreover, enhanced accuracy and throughput are acquired for the presented model in terms of reliability (95.26%) and stability (92.16%).

1. Introduction

Earthquake is among the worst natural calamities. It poses a significant threat to the economy and human life, as well as to the peaceful and persistent progress of society (Abbasi et al., 2021; Falanga et al., 2022). During the 20th century, earthquake catastrophes claimed the lives of over 2 million people worldwide[1]. Nearly 100,000 of the approximately 500,000 earthquakes that occur each year are reported and experienced by common people[2]. The death toll caused by the terrible earthquakes over the last few decades is depicted in Fig. 1[3]. To prevent such outcomes, experts from a variety of fields have collaborated to develop a reliable method of earthquake forecasting. During the analysis of seismic signals, the characteristics can be classified into three domains listed as follows:

1. Frequency domain:- The frequency domain of a signal is mathematically represented by its spectral density. To get an accurate number, all frequencies of shaking must be accounted for during the whole earthquake. Each whole number increase in magnitude corresponds to a tenfold increase in observed amplitude and a 32-fold increase in energy output.
2. Time domain:- The term "time domain" refers to the investigation of temporal relationships among mathematical functions, physical signals, and time series of economic or ecological data.
3. Time–frequency domain:- A time-domain graph depicts the evolution of a signal over time, but a frequency-domain graph displays the proportion of the signal inside each frequency band across a range of frequencies.

1.1. Problem identification

Seismology continues to face considerable difficulties in predicting earthquakes, despite its critical importance for human security. Several studies argue that an earthquake forecast must include the following;

1. A specified area or location
2. A precise period,

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1 Source: https://www.statista.com/.
2 Source: https://www.usgs.gov/observatories/.
3 Source: https://www.statista.com/chart/20443/deadliest-earthquakes-since-1900/.

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Fig. 1. Global frequency of earthquakes.

3. A defined magnitude range
4. An exact probability of occurrence

In other words, a prediction of an earthquake must include the time, location, magnitude, probability, and reason for its occurrence. The purpose of earthquake forecasts is to aid disaster control organizations in preparing for earthquakes. When a powerful earthquake is forecast, disaster control administrators must be alerted to take precautionary measures. In catastrophe preparedness, decisions and activities are centered on preventing losses. Conspicuously, a variety of earthquake prediction techniques have been implemented to reduce damage. Using several methods including precursor signals, mathematical computation, electromagnetic fields, and anomalous and animal behavior, earthquake scientists have realized the utility of accurate earthquake forecasting to society. Unfortunately, because of the complexity and unpredictability of earthquakes, conventional techniques seldom generate effective outcomes (Xin et al., 2022). Henceforth, it presents the primary motivation for the current research work. The development of monitoring techniques and computing technology acting as a driving revolution in computational engineering provides an efficient answer to earthquake prediction.

1.2. Research motivation

The current use of IoT technology has been recognized as an emergent study subject in every domain of science and engineering in response to earthquake-related losses (Bandyopadhyay and Sen, 2011; Gubbi et al., 2013). Small, low-cost sensors are utilized to collect seismic data for IoT-enabled earthquake monitoring and prediction (Abbasi et al., 2021). For early detection, sensor data is evaluated in a time-sensitive manner (Bassetti and Panizzi, 2022; Tao et al., 2022). Nonetheless, processing the enormous data contents requires a vast amount of computer resources, which are usually destroyed, unavailable, or only temporarily available in the disaster-affected area (Lin et al., 2017). The intelligent identification of real-time earthquake occurrences using stand-alone technology is difficult due to several factors, including the availability of redundant data and network services (Brous et al., 2019; Bhardwaj et al., 2019). Emerging technologies of IoT, edge computing, and cloud computing enable dynamic networks with effective data analysis to produce enhanced solutions for disaster management. Considering the time-sensitivity of monitoring earthquakes, the proposed architecture for real-time data processing incorporates Edge Computing (Cremen et al., 2021; Xu et al., 2021). It extends the cloud computing architecture to the network edge, providing benefits such as decreased delay, quality of service, location-based services, time-sensitive evaluation, and early alerts (Iwendi et al., 2020).

1.3. Major contribution

Based on the aforementioned aspects, the current architecture integrates IoT, Edge Computing, cloud computing, and predictive analytic approaches to identify earthquakes in real time and issue public safety alerts in advance (Bandyopadhyay and Sen, 2011). Fig. 2 shows the integration of 3 paradigms to realize vital service delivery aspects (Yu et al., 2017). The integration has enabled real-time accessibility, privacy, latency, and dependability for applications. The primary objectives of the proposed research are mentioned ahead;

1. Presenting a comprehensive earthquake prediction framework using sophisticated IoT–edge–cloud computing platforms to extract optimum features from complicated data.
2. Analyzing IoT data and events from IoT sensors and extending to the distant cloud platform, to enhance the data gathering and analysis processes.
3. Developing a prototype architecture to collect real-time IoT data for effective prediction systems.

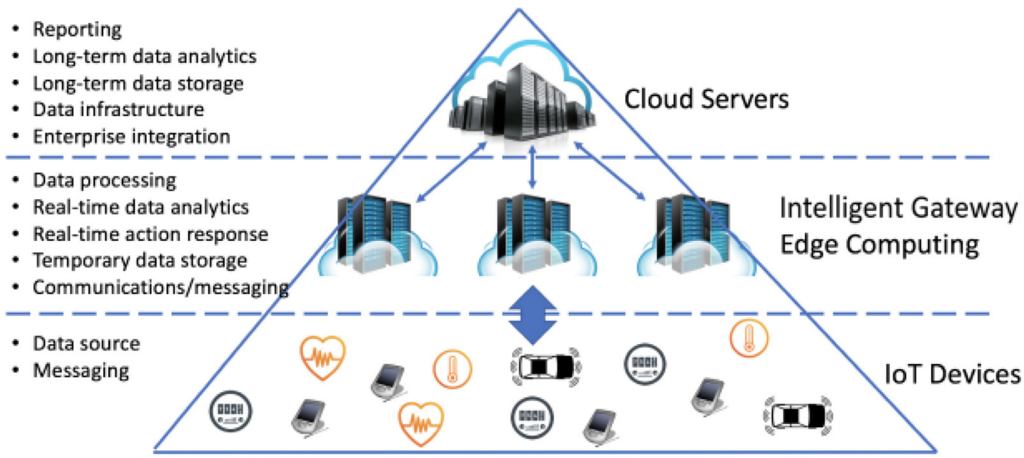


Fig. 2. IoT–Edge–Cloud layered architecture.

4. Evaluating the proposed model for performance assessment in terms of several metrics including classification efficacy, prediction efficiency, computational delay, reliability, and stability.

Paper organization. Section 2 presents a concise summary of state-of-the-art works for earthquake prediction. Section 3 describes the architectural layout of the presented model. Section 4 examines the performance assessment of the presented system. Section 5 concludes the paper with research directions for the future.

2. Literature review

Long-term and short-term earthquake forecasting has been a core research domain for several years. Numerous research on occurrences and predictions of earthquakes have resulted in dynamic results. The seismology community has developed a successful implementation system for early earthquake determination and characterization. Kumar et al. (2018) created a seismic activity identification method using the Short-Time-Average/Long-Time-Average (STA/LTA) algorithm. It established a collaborative sensing network to monitor seismic activity in a specified region. Specifically, it utilizes an activity identification approach to differentiate between seismic events and local noise. Vaezi and Van der Baan (2015) evaluated power spectral density techniques for the identification of seismic events. Liao et al. (2022) employed a Template-Matching Algorithm to enhance the effectiveness of earthquake detection. It examined vital characteristics of the earthquake using GPU architecture to expedite computations. The presented technique is computationally intensive and is limited in recognizing earthquakes. In addition, research conducted in recent years has proved the applicability of Machine Learning (ML) approaches to seismological issues. Bhargava and Pasari (2022) proposed Artificial Neural Networks for predicting earthquake magnitudes using temporal information. Additionally, prediction is performed by employing Seismic Electric Signals as input data to enhance accuracy. Shen and Shen (2021) presented convolutional neural networks for seismological event detection. The presented technique depends on the detection of earthquake signals in the temporal domain and employs the spectral features of phase to differentiate between waves. Wibowo et al. (2021) developed a P-wave discriminator to alleviate the noise trigger issue by employing two potent ML algorithms: GANs and Random Forests. Tehseen et al. (2021) introduced an ANFIS-based technique for predicting future earthquakes with a magnitude of at least 5.5. The ANFIS system was modeled using 3 algorithms including Fuzzy C-means, Grid Partition, and Subtractive Clustering. Ahamed and Daub (2021) compared numerous temporal evaluation techniques such as data network, k-nearest neighbors and multi-objective info-fuzzy for predicting the magnitude of the earthquake event based on sampled data. With the use of intelligent sensors and cloud services, advancements have been achieved in the infrastructure for sensing. Bassetti and Panizzi (2022) created distributed warning framework for the metropolitan city by combining mesh networks and seismometers. Utilizing a cooperative approach for signal processing, the presented system can distinguish between earthquakes and other forms of ground shaking in a metropolis. Roy et al. (2021) used regression techniques and a cloud-based infrastructure to forecast earthquakes in California. Sun et al. (2021) reviewed techniques for detecting earthquakes based on the study of electromagnetic waves. Several seismic factors including energy, wavelength, frequency, wave magnitude, and zones are abstracted from waves utilizing Fast Fourier Transformation to detect an earthquake. Won et al. (2020) presented an IoT device for intelligent earthquake identification. It consists of 3 major components including a high-fidelity accelerometer, an inbuilt earthquake identification system, and a Bluetooth beacon for alert generation. However, the authors did not address location awareness or latency-sensitive issues. Moreover, the authors used a seismological software package as a server application for data communication. Cremen et al. (2021) presented the early earthquake warning (EEW) system by utilizing a Virtual Seismologist. Imeraj et al. (2022) designed and implemented an embedded seismograph for efficiently and effectively supporting seismological and geophysical data collection networks.

2.1. Research gaps

Catastrophe organizations prioritize disaster management in order to limit the loss of property and lives to the greatest degree feasible. Several viable decision-making models for forecasting earthquakes in real time have been envisioned using IoT–Edge–Cloud computing. Nevertheless, based on the extensive literature review, Table 1 identifies some significant research gaps linked to the current study area. In addition, some of the most critical barriers are as follows:

1. Researchers have not explicitly studied the assessment of earthquake prediction in a real-time scenario.
2. Minimal research effort has been undertaken for earthquake real-time detection over a time-scale.
3. The majority of research is restricted to monitoring, and less work is undertaken on the analysis of IoT data for accurately predicting earthquakes in real-time and enhancing public warning issuance.
4. The inclusion of ANFIS for accurate earthquake magnitude prediction is an additional component that has been lightly investigated in contemporary research.

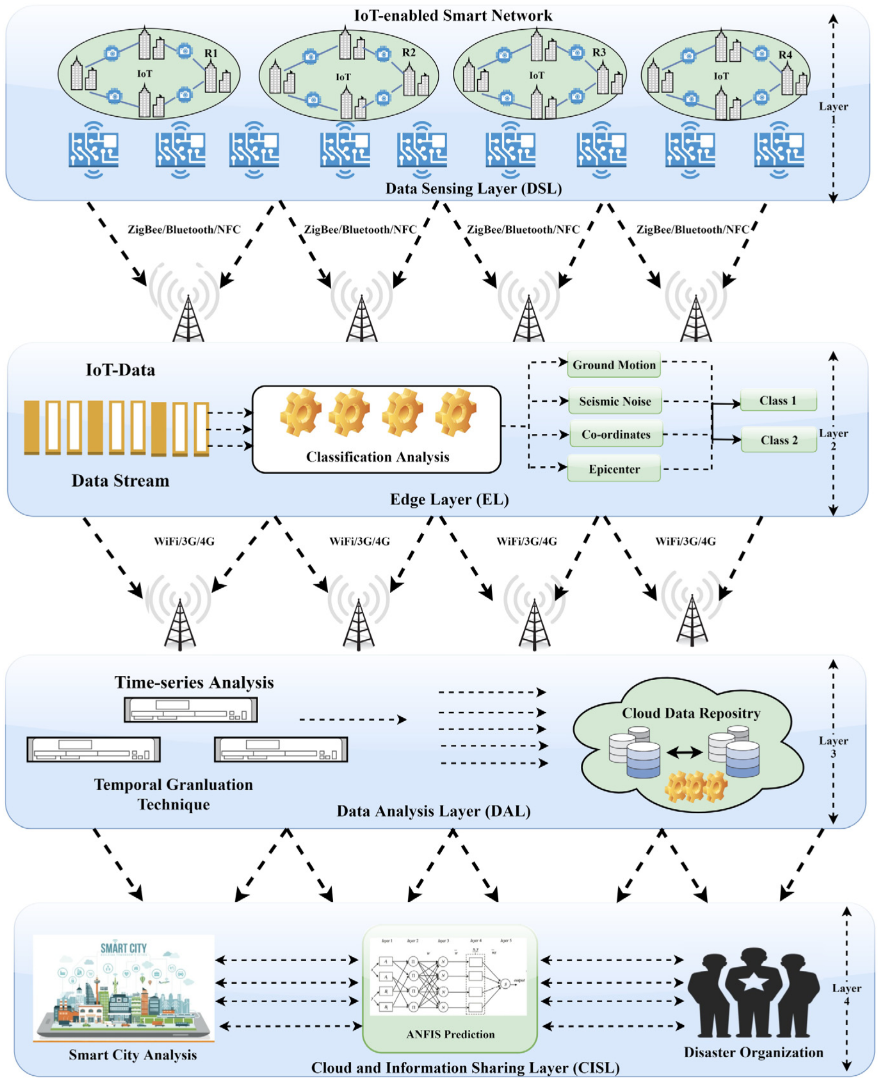


Fig. 3. Proposed model.

3. Proposed framework

Fig. 3 presents a layered framework of the proposed IoT–centric edge–cloud collaborative system for earthquake detection for monitoring seismic signals efficiently. It comprises several layers including the Data Sensing Layer (DSL), Edge Layer (EL), Data Analysis Layer (DAL), and Cloud and Information Sharing Layer (CISL). DSL is responsible for distributing sensors over the geographical region to gather seismic data in its raw form. The cumulative data are sent to EL for the classification of earthquakes in real time. DAL enables efficient extraction of useful data instances based on a temporal manner. CL is responsible for accumulating compiled data for forecasting and monitoring results, thereby assisting disaster response organizations in controlling earthquake loss.

3.1. Data sensing layer (DSL)

DSL is the physical layer for gathering and transforming data into comprehensible digital signals by utilizing IoT devices. It detects and transforms seismic characteristics into useful information. An efficient earthquake detection framework incorporates geological and location factors.

1. *Geological Attributes:* It depicts the geological state in the region with a substantial effect on earthquake initiation. It comprises data on seismic waves, ground motion, ground-level variations, vibration noise, and a temporal evaluation of deformations.
2. *Position Attributes* The locational latitudes and longitudes of the afflicted region are utilized to pinpoint the precise geographic area of the earthquake's epicenter. It includes latitude, longitude, and epicenter.

Table 2 displays the described specific earthquake parameters and respective IoT sensors. For earthquake prediction, sensors installed in the research zone measure the earthquake-inducing characteristics.

3.2. Edge layer (EL)

EL layer aligned between IoT devices and DAL. It is comprised of edge gateways and databases to enable dynamic real-time processing and storage along with data transmission to the cloud server. Numerous modules are integrated for EL-based computational analysis. It includes filtering data, extracting characteristics, decreasing sizes, and categorizing events for seismic prediction. EL is crucial for preventing data transmission to the cloud repository for temporal computations.

3.2.1. Extracting features

During seismic data accumulation, it is interrupted by a variety of distorting sounds of motion artefacts, baseline drift, and instrumentation noise created by the device. For precise and exhaustive earthquake

Table 1
State-of-the-art comparison (A Exist, – Do-not Exist).

Reference	Kumar et al. (2018)	Vaezi and Van der Baan (2015)	Liao et al. (2022)	Bhargava and Pasari (2022)	Tehseen et al. (2021)	Wibowo et al. (2021)	Shen and Shen (2021)	This Work
Sensing technology	A	A	A	A	A	A	A	A
Edge computing	–	A	A	–	A	–	–	A
Classification	–	–	–	–	–	–	–	A
Storage	A	A	A	A	–	–	A	A
Temporal analysis	–	–	–	–	–	A	A	A
Quantification	A	A	A	A	A	–	A	A
Delay latency	–	–	–	–	–	–	–	A
Reliability	–	–	–	–	–	–	–	A
Predictive behavior	–	–	A	–	A	–	–	A
Security	–	–	–	–	–	A	–	A
Stability	–	–	A	–	–	–	–	A

Table 2
Earthquake attributes.

Attribute	Detail	IoT-Sensors
Ground motion	Motion of the ground due to earthquake	Seismic sensors
Seismic noise	Ground shaking noise	Seismometers
Groundwater levels	Earthquake result in the water level rise leading to Tides	Water level sensors
Longitude	Coordinates for the location of the earthquake	Location sensors
Epicenter	Focus point of the earthquake	Epicenter sensor
Latitude	Coordinates for the location of the earthquake	Location sensors

Table 3
Extracted time features with mathematical description.

Feature domain	Definition	Mathematical formula
Time domain	Standard deviation	$\sigma\mathrm{x}= \sqrt{\frac{1}{n-1} \sum_{i=1}^{n}(x_i - \mu_x)^2}$
	Skewness	$S_k = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{(x_i-\mu_x)}{\sigma x} \right)^3$
	Kurtosis	$K = \left(\frac{1}{n} \sum_{i=1}^{n} \left(\frac{(x_i-\mu_x)}{\sigma x} \right)^4 \right) - 3$
	Variance	$V = \frac{1}{n-1} \sum_{i=1}^{n} \lvert x_i \rvert^2$
	Root mean square	$\mathrm{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \lvert x_i \rvert^2}$
	Mean absolute value	$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} \lvert x_i \rvert$
	Approximate entropy	$\mathrm{AEn(m,\ r,\ N)} = \left[\phi^m(r) - \phi^{m+1}(r)\right]$
	Energy entropy	$\mathrm{EEn} = -\sum_{i=1}^{n} p_i \ \log\ p_i$
	Waveform length	$\mathrm{WL} = \sum_{i=1}^{n-1} \lvert x_{i+1} - x_i \rvert$

Table 4
Extracted frequency features with mathematical description.

Feature domain	Definition	Mathematical formula
Frequency domain	Peak frequency	$f_p = \arg\ \max \lvert F_i(f) \rvert^2$
	Mean frequency	$f_m = \frac{\sum_{i=1}^{N} f_i P_i}{\sum_{i=1}^{n} P_i}$
	Mean power	$P_m = \frac{\sum_{i=1}^{N} P_i}{n}$
	Spectral moment of order-2	$\mathrm{SM} = \sum_{i=1}^{N} P_i f_i^2$
	Total power	$\mathrm{TP} = \sum_{i=1}^{n} P_i$

detection, it is required to filter out high-frequency modules and noise sources. The seismological data were analyzed using a 4th order filter to remove the power-line noise. Feature extraction is the procedure of extracting important aspects from unprocessed input values and condensing in reduced features. The success of seismic event categorization is highly dependent on the selection of relevant characteristics. Using the seismic signal to interpret features, a Discrete Wavelet Transform (DWT) of 5 levels is used for extracting unique characteristics from DWT coefficients of varying sizes. Due to the non-stationary character of the DWT, it is used for the time–frequency signal analysis. The DWT employs a large temporal window for reduced frequency and a short-temporal window for higher frequency. It decomposes the initial signal in a wavelet coefficient that represents the signal vector behavior at multiple frequencies. At the initial level, the seismic signal is assessed for high-low pass filtration. This procedure is repeated for each level of decomposition. It turns a signal into approximate and detailed coefficients. During the analysis of seismic signals, the characteristics can be classified into three domains listed as follows:

1. Frequency domain,
2. Time domain,
3. Time–frequency domain

Time domain: From seismic datasets, time-domain characteristics are extracted explicitly. Time domain features are extracted by calculating Standard deviation, Skewness, Kurtosis, Variance, Root mean square, Mean absolute value, Approximate entropy, Energy entropy, and Waveform length. The mathematical description of all the matrices is presented in Table 3.

Frequency domain: The Power Spectral Density of a seismic wave is employed by calculating Peak frequency, Mean frequency, Mean power Spectral moment of order-2, and Total power as presented in Table 4.

Time-Frequency domain: At each level of DWT decomposition, time–frequency characteristics are retrieved by calculating the Standard deviation of the wavelet, Average wavelet power, Mean of the absolute value, and Entropy. The mathematical description is provided in Table 5.

3.2.2. *Attribute reduction*

After extracting, the attribute dimension is large thereby elevating classifier complexity and lowering error convergence. To reduce computational complexity and enhance generalization on unlabeled data, it is essential to reduce the number of features to a minimum. Using a feature selection strategy, it is possible to reduce attribute dimension. The purpose of feature identification is to (i) Dimension reduction, (ii) Eliminate extraneous characteristics, (iii) Minimize classifier data, and (iv) Enhance classification performance. In the presented research, correlation-based Feature Selection (CBFS) is employed to determine usable features. CBFS is a feature identification strategy for determining the reduced characteristics that are potentially relevant to a given task. CBFS selects the vital characteristic for increased precision, while simultaneously lowering the number of features and delays. The important component of the CBFS technique is a heuristic for evaluating the value of the attribute subset defined as follows:

$$\mathrm{MS\ (Merit)} = \frac{SDG}{\sqrt{L + L(l-1)SGG}}$$

Table 5
Extracted time–frequency features with mathematical description.

Feature domain	Definition	Mathematical formula
Time-Frequency domain	Standard deviation of wavelet	Coefficients in each level: $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(c_i - \mu)^2}$
	Average wavelet power	Coefficients in each level: $P_i = \frac{1}{N}\sum_{i=0}^{N}(c_i)^2$
	Mean absolute value	Coefficients in each decomposition: $\mu_i = \frac{1}{N}\sum_{i=1}^{N}(c_i)$
	Entropy	$EN = \sigma = \sum_{i=1}^{N}(c_i^2 log(c_i^2))$

where L is the number of features, SGG represents the mean feature-to-feature correlation, and SDG represents the mean feature-to-class correlation. It emphasizes the importance of particular characteristics while class label evaluation. Additionally, it reduces duplicate and unnecessary characteristics that are insufficient class predictors. The CBFS method is explained as follows:

1. Calculate the correlation between the feature class and the correlation between features.
2. Evaluate the merit value of each feature.

Using the outcomes of the previous phase, the subset with the highest MS is selected. The selected subset of features and respective labels constitute an appropriate feature set. To minimize feature dimension, the Genetic Algorithm (GA) is utilized as a searching approach with CBFS as an evaluating function. The GA is a probabilistic, particular search strategy capable of identifying vast search areas, which is typically required in attribute identification. In the GA mechanism, merit measures are evaluated for nine distinct attribute subsets. This process is repeated at different times such that the highest merit value is selected. Ten characteristics (greatest merit value) have been selected for categorization.

3.2.3. Event classification

One of the most vital tasks in the presented model is the categorization of the attributes in distinct seismic activities namely *earthquakes* and *non-earthquake*. Various classification techniques of clustering, discriminant analysis, and neural networks, have been evaluated for the feature classification process. Even though the strategies were helpful for a variety of classification issues, the Bayesian Belief Model (BBM) classifier performed best in the current research. Additionally, the classification work is essential for reliably forecasting earthquakes with better precision and reduced classification time to provide real-time services. The basic layer collects data from numerous IoT devices on catastrophic occurrences. The gathered data is examined to ascertain the probability of a calamity occurring. BBM is an efficient instrument for determining the probability of earthquake detection (ED) (Qazi et al., 2018). BBM uses current research data to establish the Probability of Earthquake Detection, a probabilistic metric for ED determination (PoED).

Definition 1 (*Probability of Earthquake Detection(PoED)*)**.** It is a probabilistic metric to detect the magnitude of an earthquake in real-time at a particular instance of time δt. Specifically, the PoED provides a methodical measurement of an unfavorable environmental occurrence

Definition 1 determines a quantifiable metric for the detection of the earthquake in real time. In other words, PoED evaluates the parameters for the real-time prediction of the earthquake. In the current study, the BBM method is preferred for classification because of its accuracy, feasibility, and efficiency.

3.2.4. BBM-based mathematical analysis

BBM is utilized to categorize the datasets into distinct categories. As previously stated, two types are characterized using distinct seismic parameters. Let a vector $E_i = (E_1, E_2, \dots, E_n)$ represent an instance of the data, where E_i represents the earthquake variable i, assuming that all parameters related to the earthquake are not mutually dependent. The conditional likelihood that an earthquake will be detected E_i of type D_j is represented by $P(\frac{D_j}{E_1, E_2, \dots, E_n})$. Numerous input parameters are accessible, and a specific metric instance of earthquake detection might have a substantial value; hence, the above-mentioned formula may lead to inconsistency in earthquake magnitude detection in real time. Following this, the revised BBM is stated as

$$P(\frac{D_j}{E_i}) = \frac{P(D_j)P(E_i/D_j)}{P(E_i)}.$$

However, the probability of $P(D_j)P(E_i/D_j)$ can be improved based on joint probability function as

$=> P(D_j)P(E_i/E_j) = P(E_1, E_2, \dots, E_n, D_j)$
$=> P(E_1/E_2, \dots, E_n, D_j)P(E_2, \dots, E_n, D_j)$
$=> P(E_1/E_2, \dots, E_n, D_j)P(E_2/E_3, \dots, E_n, D_j)P(E_3, \dots, E_n, D_j)$
$=> P(E_1/E_2, \dots, E_n, D_j)P(E_2/E_3, \dots, E_n D_j), \dots, P(E_{n-1}/E_n, \dots, E_n D_j) * P(E_n/D_j)P(D_j)$

In addition, it is expected that each characteristic E_i of the variable for disaster identification is independent of any other measure E_j i.e. $i \neq j$. Then $P(E_i/E_{i+1}, \dots, E_n, D_j) = P(E_i/D_j)$

Therefore, the joint probability is described as follows:

$=> P(D_j) = \Pi_{i=1}^{n} P(D_j)P(E_i/D_j)$
$=> P(\frac{D_j}{p}) = \Pi_{i=1}^{n} P(D_j)P(E_i/D_j)/P(E)$

In the equation described above D_j denotes the class 1 and class 2 parameters.

3.3. Data analysis layer

To monitor earthquake data, DAL's purpose is to extract meaningful information from the data repository. The proposed model aims to provide real-time disaster relief services. Earthquake vulnerability is analyzed in greater detail by abstracting temporal data segments. Using Temporal Data Mining, valuable data segments may be retrieved for further analysis. Time-series data may be effectively analyzed using Temporal Data Mining techniques (Xiao et al., 2021; Xing et al., 2022).

Definition 2 (*Temporal Granule (U^*)*)**.** Given the parametric measure in the temporal window of Δt, then U^* is represented as the accumulation of data measures for earthquake-oriented parameters corresponding to every instance of time $t \in \Delta t$ and is denoted as $(t_1, w_1)(t_2, w_2), \dots, (t_n, w_o)$.

Several data segments that affect the earthquake prediction can be abstracted effectively using the data abstraction of Temporal Granule (U^*). Data values may be effectively assessed for further in-depth examination using such conceptualization. Disaster relief organizations can use the formulation to give timely and effective care to the people in the event of an earthquake event. Fig. 4 depicts a quick summary of temporal granulation.

3.4. Cloud layer (CL)

CL is vital in the proposed system. As a result of the restricted storing ability and computation capabilities of the edge layer, seismic event data is kept and processed on Cloud servers as assembled records. It is comprised of two parts: (1) Magnitude forecasting and (2) Cloud storage.

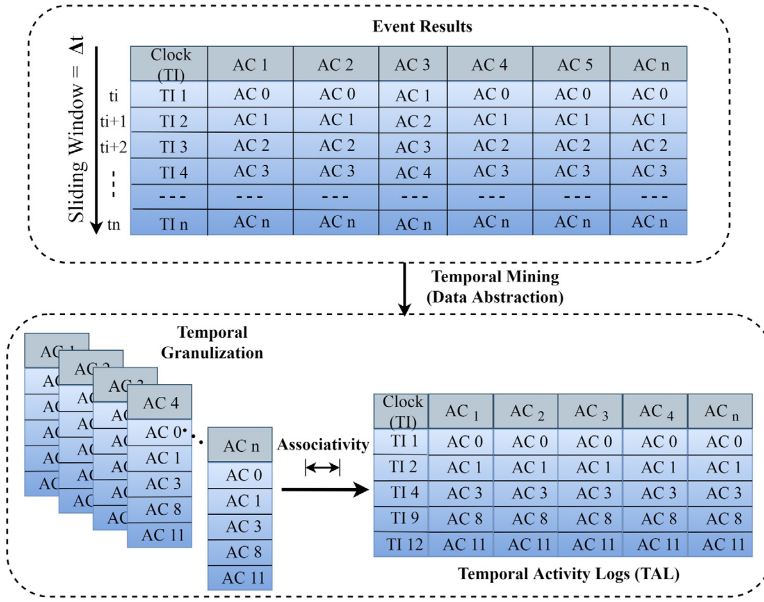


Fig. 4. Temporal analysis.

3.4.1. Magnitude forecasting

In the current research, the ANFIS paradigm is utilized for the quantification of identified earthquakes. It is a culmination of ANN and fuzzy theory that integrates the learning powers of a neural system with the inference capabilities of fuzzy logic and superior knowledge representation to improve prediction capacity. To find the ideal membership function distribution, the ANFIS technique can generate an input–output mapping based on expert information. In this manner, the mathematical formulation of the ANFIS model is depicted ahead.

3.4.2. Adaptive neuro-Fuzzy inference system (ANFIS)

Numerous academics in various domains employ the ANFIS paradigm for predictive decision modeling. ANFIS is typically employed to address exceedingly complicated and nonlinear problems. Fig. 5 depicts the 5-layer ANFIS structure with seven input attributes. Fuzzy logic enables multi-value input from a parental input variable expressing the connection between a single value set and a collection of additional values. The suggested system uses a fuzzy inference model for non-linear vector input. Each attribute is evaluated within a particular temporal frame using the ANFIS model. As an illustration, the data measures for evaluating the earthquake in a certain time–space frame are provided to the ANFIS, which then calculates its prediction measure.

(a) Fuzzification (Layer 1): The initial layer is the fuzzy layer which employs membership functions to turn the input into fuzzy sets. Each adaptive node in this layer is depicted as:

$$N_k^1 = \mu H_k(x) \tag{1}$$

where N_k^1 is the gaussian function, x is the node-specific input value k, and H_k is the linguistic parameter associated to a node. Moreover, the first layer is provided with temporal measures for different earthquake-oriented attributes.

(b) Product rule (Layer 2): By implementing the product operation, the nodes pass the input to the next layer and are represented mathematically as;

$$N_k^2 = \mu A_k(x) \times \mu B_k(y),\ k = 1,2 \tag{2}$$

where $A_k(x)$ and $B_k(y)$ represents the nodes in layer 2.

(c) Normalization (Layer 3): Each node computes the ratio of the firing strength rule to the total of all firing strength rules. The firing strength is denoted by w_j' and is further standardized as follows:

$$N_k^3 = w_k' = \frac{w_j}{w_1 + w_2} for\ k = 1,2 \tag{3}$$

(d) De-fuzzification (Layer 4): This layer has the responsibility for assessing the contribution to the final output of the kth rule. The corresponding structured consequent variables are classified as the cj, dj and rj parameters. The de-fuzzification function in this layer is as follows:

$$N_k^4 = w_k' k_k = w_k'(c_k x + d_k y + r_k)\ for\ k = 1,2 \tag{4}$$

(e) Output generation (Layer 5): It is the output layer for accumulating all de-fuzzification outputs and computes the finalized result. N_k^5 as denoted in Eq. (5);

$$N_k^5 = \sum w_k' g_k = \frac{\sum_k w_k g_k}{\sum_k w_k} \tag{5}$$

3.4.3. Cloud backup

This component is responsible for assembling the findings of the seismic event outbreak analysis including earthquake magnitude. It can help seismologists, emergency responders, and disaster management agencies to mitigate and handle earthquakes more efficiently.

3.5. Information sharing

The cloud-based findings are accessible to disaster management agencies, emergency responders, government organizations, and other relevant authorities, allowing them to act swiftly to reduce the repercussions. A gateway linked to the internet is utilized to transmit the assembled data to the relevant authorities. From the cloud layer, evaluated data are transferred directly to the gateway. The gateway can then combine the data and transmit it through the internet to a central platform maintained by the relevant Emergency Response Teams (ERT). These data may be accessible via the ERT's digital website to obtain the most information possible regarding the catastrophe site and its occurrences. Authorities adopt short-term and long-term strategies to counteract and alleviate the negative consequences of the earthquake based on the estimation of the situation's urgency.

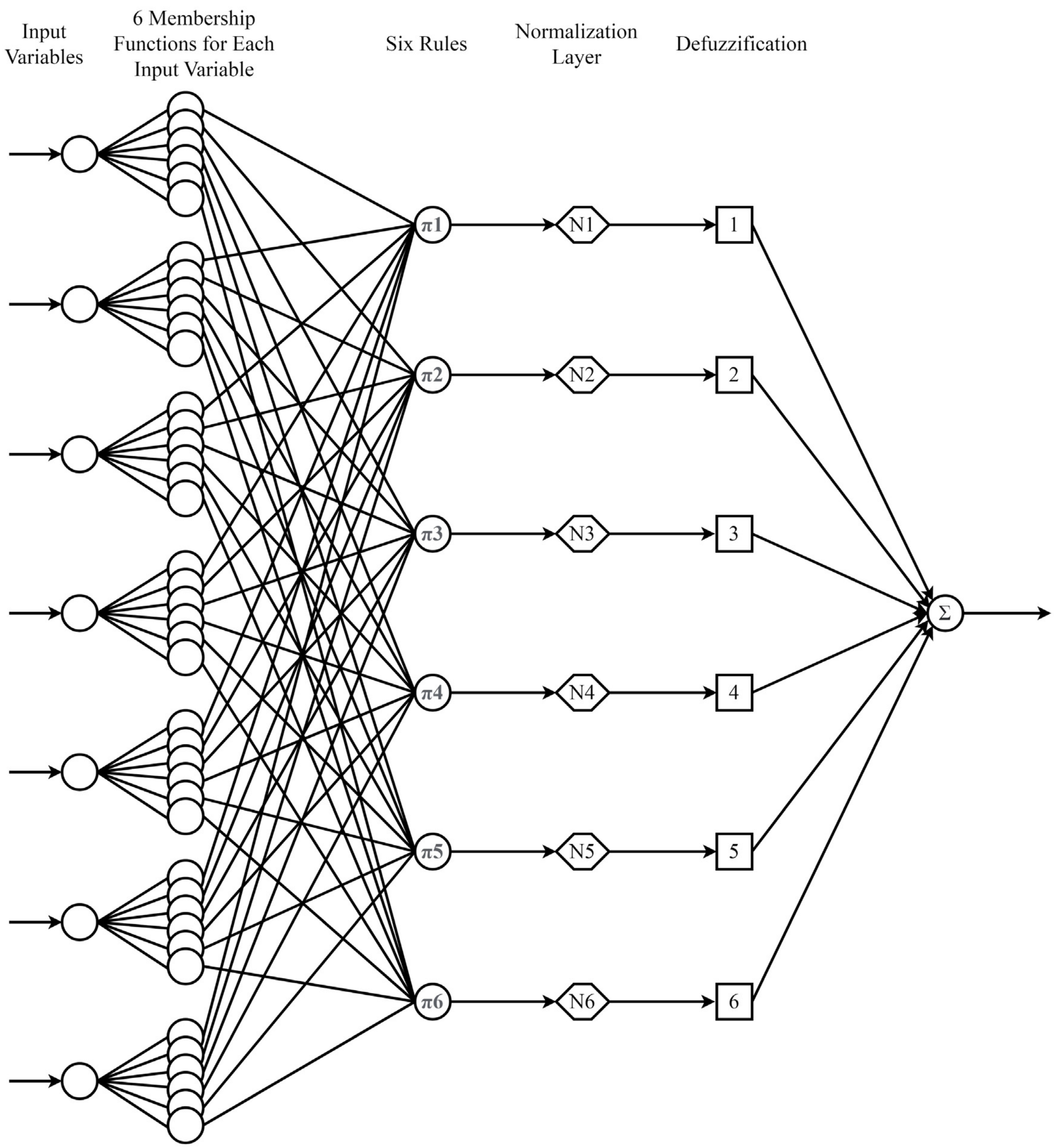


Fig. 5. Generalized ANFIS model.

4. Experimental simulation

The implementation design and evaluation of the proposed model are described. The following tasks are computed for the estimation of the performance of the proposed model. (a) Feature extraction results, (b) ANFIS-based magnitude forecasting results, (c) Feature extraction results, (d) Classification effectiveness at the edge layer, (e) Prediction efficiency, (f) Reliability, (g) Stability of the proposed system, (h) Computational complexity.

4.1. Data compilation

The Stanford Earthquake Dataset (STEAD) database[4] contains information on several seismic and geological characteristics. STEAD is a massive worldwide dataset comprised of 2 seismogram-labeled set groups. The first set depicts earthquake waveforms, whereas the other set depicts waveforms that are not associated with earthquakes. The current study utilized approximately 150000 waveforms, including 70000 earthquake waveforms and 30000 no-earthquake waveforms obtained at epicenters ranging from 0.0 to 300.0 km. Each wave consists of 7000 samples with a length of 2 min and a sampling frequency of 99 hertz. In addition, a location attribute containing data is extracted from (Mousavi et al., 2019).

Furthermore, a network topology is designed to evaluate the efficacy of the proposed solution by following the concept of the IoT–Fog–Cloud tier. Fig. 6 depicts the actual testing setup used to perform the experiments. Fog cells, fog nodes, sensors, and fog–cloud middleware-based four types of devices are part of the topology. The middleware is executing on a system which is connected to the OpenStack cloud infrastructure and creates the top tier of the topology. Raspberry Pis are used to arrange the remaining configuration elements. Fog control nodes (FCN) are the root fog coordinator nodes for all nearby fog devices that handle data from integrated IoT devices. The IoT-connected devices in this setup are sensor modules that are linked to the appropriate Raspberry Pie.

[4] Source: https://github.com/smousavi05/STEAD.

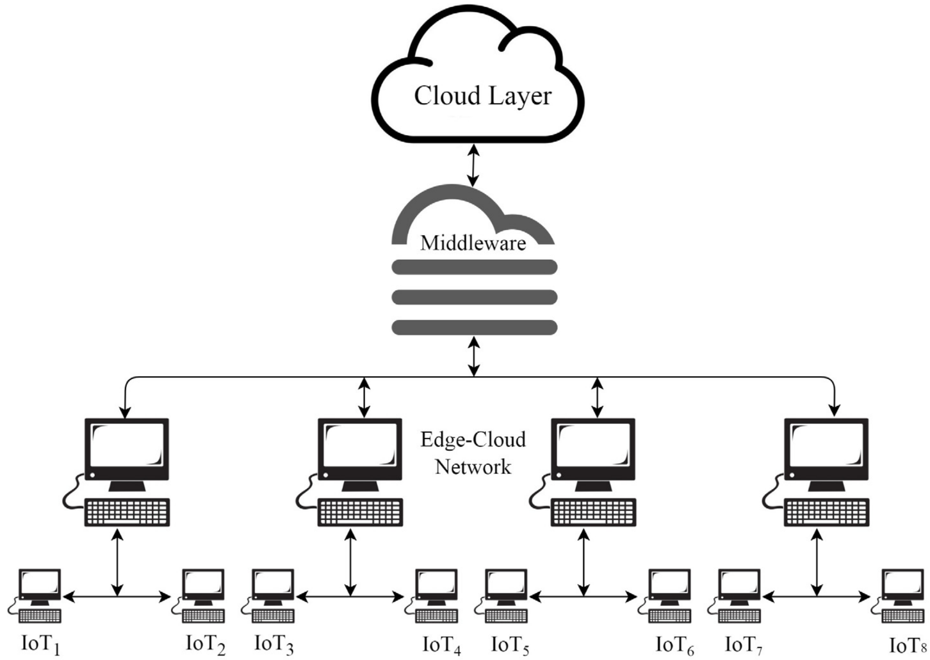


Fig. 6. Designed topology.

Table 6
Seismic signal-based 5-level DWT decomposition.

Decomposition levels	Frequency (Hz)	Coefficients
0	26–51	D1
1	11.802–26	D2
2	8.062–11.802	D3
3	5.273–8.061	D4
4	0–0.5273	A4

Combining and storing datasets on Amazon EC2 to generate the finalized data. The stages required in integrating disparate datasets to generate a single earthquake parameter dataset are depicted in Fig. 7.

4.2. Feature extraction results

The Discrete Wavelet Transform (DWT) is utilized for obtaining seismic signal characteristics. It separates the seismic signal into several sub-signals with varying frequencies. Identifying wavelet function and the correct degrees of decomposition is essential when utilizing DWT to analyze seismic data. In the proposed model, the degrees of decomposition are set to 4, and the wavelet function evaluated is DB4, which is appropriate for seismic signal processing. Table 6 depicts 5 levels of DWT and decomposition frequency bands. Calculating and analyzing the DWT coefficient is performed with MATLAB. Fig. 8 depicts the 5 unique sub-signals of the seismological data, together with one approximation coefficient A4 and 4 detailed coefficients DI–D4. Additionally, the original attribute data is created by abstracting the 18 conventional characteristics. Based on the approximation and detailed coefficients over all subbands, the estimated value is 3.1.

4.3. Feature reduction

In the current study, implementation is performed for the CBFS with the GA search method. The CBFS method assigns the highest measures to feature subsets with the class characteristic but are very moderately connected. WEKA tool is used as a searching strategy using CBFS as a subset assessment mechanism (fitness function). The number of significant features selected by the CBFS–GA for extracted attribute data is displayed in Table 7. Based on the highest merit score and standard deviation value, the features for the reduced feature set are determined to be 10.

Table 7
CBFS estimation.

S.no	Feature	Domain	Mean
1	Average power of wavelet coefficients	Time-Frequency	0.397, 0.020
2	Energy entropy	Time-Frequency	0.382, 0.027
3	Mean power	Frequency	0.303, 0.026
4	Entropy	Time	0.329, 0.046
5	Root mean square	Time	0.476, 0.031
6	Waveform length	Time	0.296, 0.09
7	Peak frequency	Frequency	0.375, 0.0.35
8	Mean of the absolute value	Time-Frequency	0.307, 0.053
9	Spectral moment of order-2	Frequency	0.579, 0.029
10	Mean frequency	Frequency	0.240, 0.063

Table 8
BBM confusion matrix.

Classification	Earthquake	No-Earthquake
No-Earthquake	0.27	0.73
Earthquake	0.81	0.7

4.4. Classification effectiveness: Edge layer

The suggested approach distinguishes between earthquakes and other types of seismological events using a BBM Classifier at the EL Layer. The BBM classifier was trained using 5000 seismic data using WEKA, with 15 iterations used to speed up the training process. In Table 8, it can be seen that many instances were correctly or incorrectly classified as positive or negative. In addition, the collected data is used to develop statistical measures like accuracy, responsiveness, and selectivity.

Table 9 shows the outcome of the trained classifier's classification of the training dataset. The results show that 97% of all seismic events are correctly diagnosed, whereas 3% are incorrectly labeled as something other than earthquakes. Nearly all earthquake data points are correctly recognized, with only 7% mislabeled as anything other

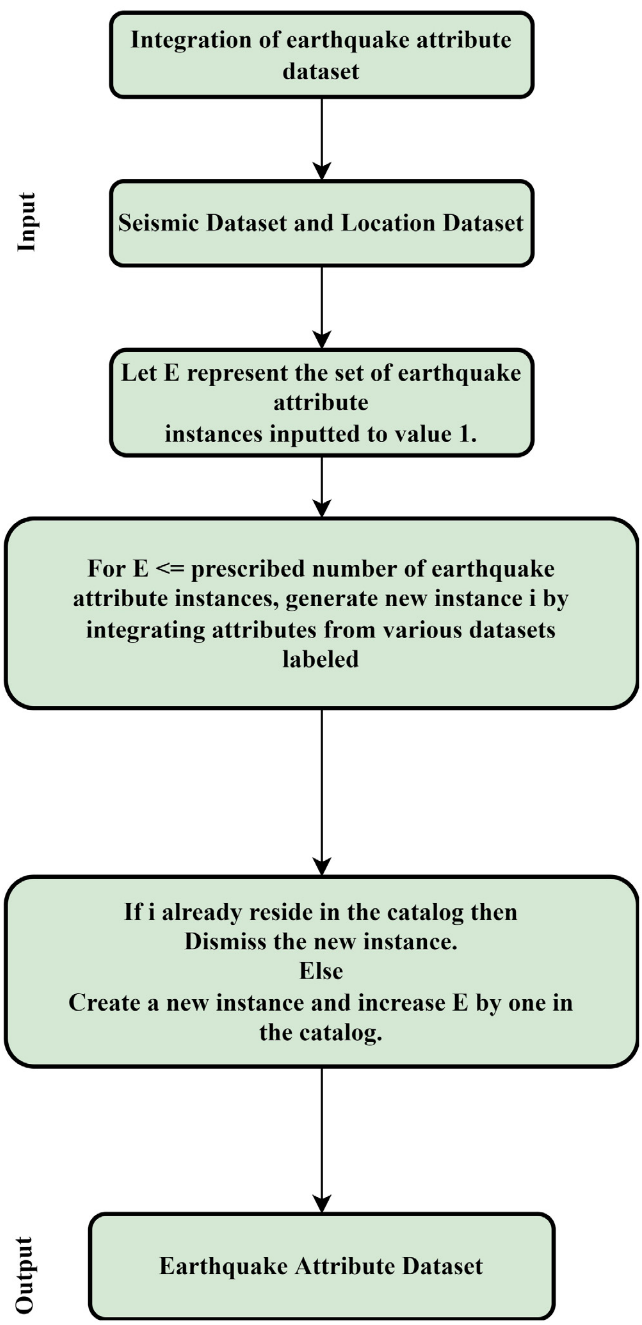


Fig. 7. Algorithm 1 Integration of earthquake attribute dataset.

Table 9
BBM classification performance.

S.no	Seismic events	Sensitivity(%)	Specificity(%)
1	Non-Earthquake	93	98.51
2	Earthquake	97	99.54

than earthquakes. In addition, cutting-edge methods like the Support Vector Machine and the C4.5 decision tree (DT) algorithm have been compared to the BBM in terms of performance.

Table 10 displays the sensitivity, specificity, and precision of several classifiers for identifying different types of seismic events. In the current study, the BBM classifier registered the greatest classification precision at 92.52%, the highest mean sensitivity at 91.72%, and the highest mean specificity at 91.01%, making it a strong candidate for earthquake detection. The BBM classifier has a large area under the ROC curve compared to other methods. Fig. 9 shows the amount of time it takes classifiers to make their classifications in relation to the total quantity of seismic samples. The BBM classifier's classification time grows more slowly in proportion to the number of samples than that of other classifiers. The BBM classifier is well-suited for both earthquake and non-earthquake classification in real-time since its cumulative classification time remains below normal ranges.

4.5. Prediction analysis

As discussed before, ANFIS is composed of 5 layers, 3 inputs (latitude, longitude, and depth), and 1 output (magnitude forecast). The ANFIS model was run in MATLAB R2019b for the simulation purpose. The suggested model's ANFIS training parameters are described in Table 11. Fuzzy networks utilize backpropagation and a hybrid algorithm to fine-tune the membership function's variables in order to learn from data. For training ANFIS models, the Gaussian membership function is used. The learning procedure modifies the membership function's parameters. For a given set of attributes, the accuracy of the output data is determined by the gradient vector. The error rate is decreased by adjusting the settings after receiving the gradient vector. It is the sum of the squared deviations between the expected and actual outputs that constitute the error. To test how well ANFIS predicted earthquake magnitudes, a 10 Fold cross-validation technique is employed. Further, the training method is iterated inside each fold throughout several epochs until the training error aim is achieved or a maximum number of iterations is reached. The average percentage of mistakes across all folds and periods is shown in Fig. 10. The inaccuracy in the forecast was determined by subtracting the measured Richter magnitude from the ANFIS-predicted result i.e.

$$Error = Actual\ value - Predicted\ value$$

Error reduction is analyzed, therefore training is halted at the 55th epoch. The performance metrics acquired by the ANFIS model for testing and training data are displayed in Table 12. Coefficient of Determination (R2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) values of 0.908%, 0.915%, and 0.895 respectively, indicate that the ANFIS model produced acceptable results for forecasting earthquake magnitude. Moreover, several statistical parameters are acquired for determining the prediction efficiency. These include sensitivity, specificity, accuracy, and precision. For determining the overall values of the statistical parameters, the proposed model is compared with state-of-the-art models namely, K-Nearest Neighbor (K-NN), Artificial Neural Network (ANN), and Support Vector Machine (SVM). The plot in Fig. 11(a, b, c and d) denotes the accuracy, precision, sensitivity, and specificity of the proposed model. Computing over an average of the number of instances, the presented model was able to attain the highest accuracy value of 95.85%, the precision of 96.26%, the sensitivity of 96.89% and specificity of 95.48% which in comparison to K-NN, cANN, and SVM is better. The findings indicate that utilizing the ANFIS model to make predictions is a viable strategy, as the results are significantly more exact and accurate.

4.6. Reliability analysis

Reliability ensures dependability for the current domain of research. Decision-making is vital for effectiveness. Henceforth, the performance of reliability analysis must be assessed for better efficacy. Fig. 12 shows the results of the reliability assessment simulation. Efficiency levels are registered with greater values approximating 95.26% for the provided model when the number of datasets for experimental implementation increases. The suggested approach appears to be more reliable over large datasets.

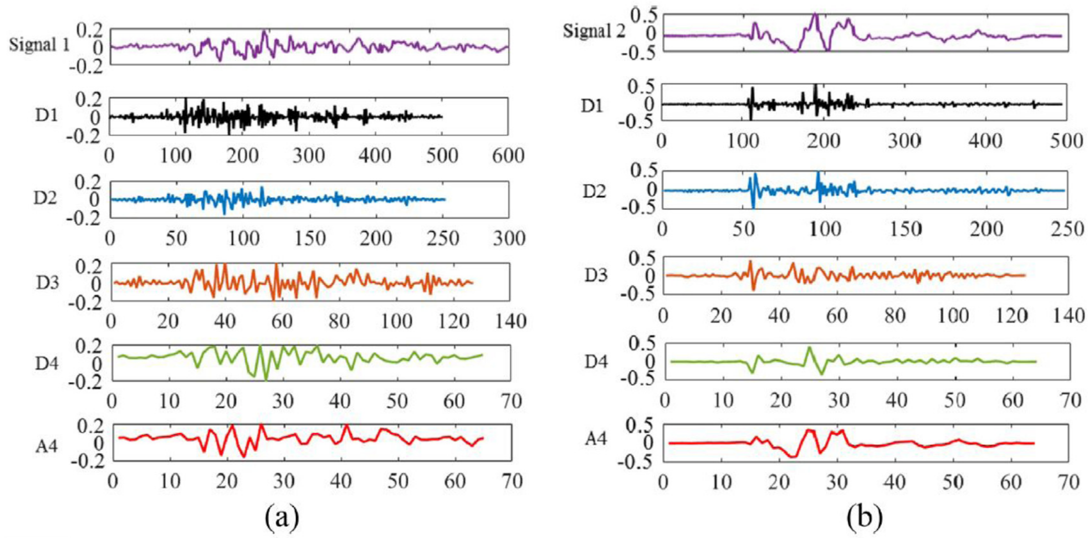


Fig. 8. Seismic signals; (a) Earthquake, (b) Non-earthquake.

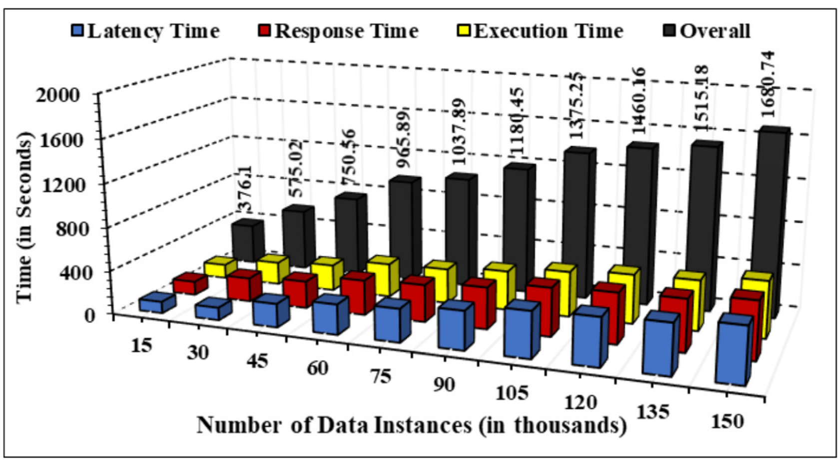


Fig. 9. Computational delay.

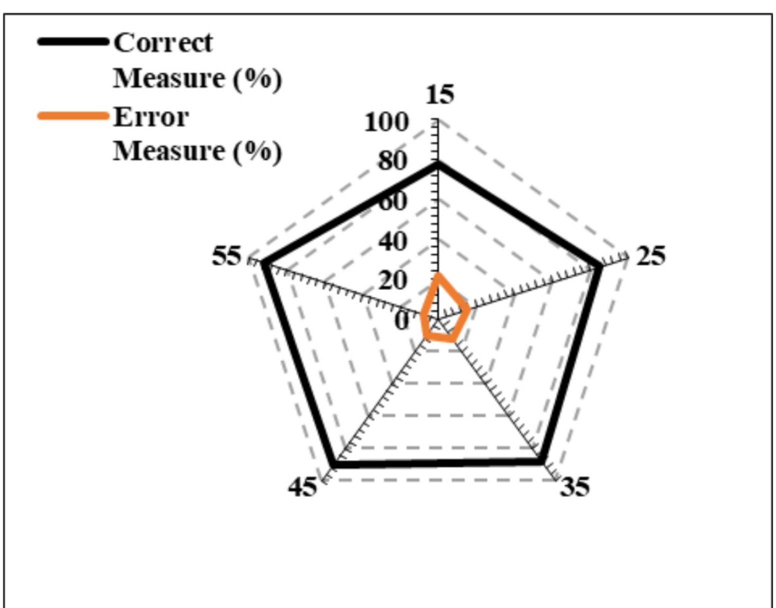
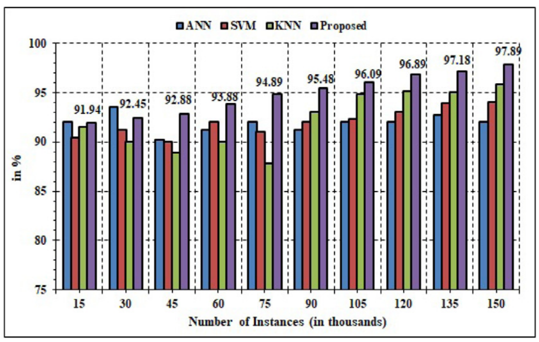


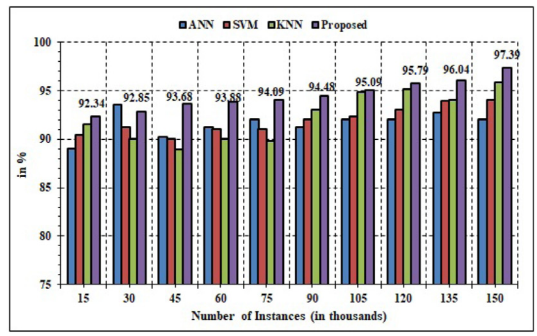
Fig. 10. Computational error.

Table 10
Classification Efficiency; (Precision (Prec), Specificity (Spec), Sensitivity (Sens)).

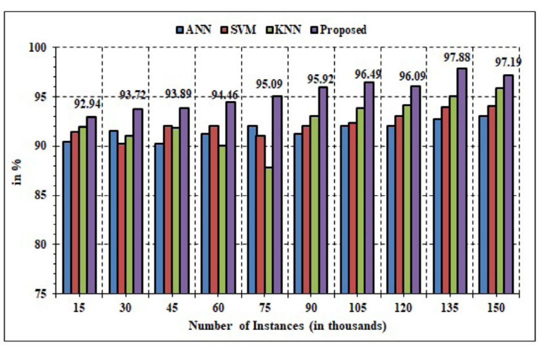
Model	BBM Classifier			C4.5 DT			Support vector machine		
Dataset	Prec	Spec	Sens	Prec	Spec	Sens	Prec	Spec	Sens
15000	95.55%	92.05%	93.92%	92.92%	89.02%	90.77%	92.52%	89.15%	90.11%
30000	92.79%	91.95%	92.32%	91.52%	91.22%	91.72%	91.02%	91.79%	91.05%
45000	93.57%	91.99%	92.52%	91.52%	90.33%	92.35%	90.07%	90.53%	92.09%
60000	93.73%	90.95%	91.32%	92.52%	89.15%	90.59%	92.32%	90.73%	90.59%
75000	91.57%	92.55%	92.55%	91.22%	90.22%	92.09%	91.75%	91.27%	92.39%
90000	92.32%	90.32%	91.32%	92.21%	91.15%	91.07%	92.77%	91.02%	91.93%
105000	93.92%	89.93%	91.31%	91.27%	89.92%	90.25%	91.15%	90.79%	89.17%
120000	92.32%	90.55%	92.72%	92.12%	89.55%	91.15%	92.07%	89.99%	91.35%
135000	91.95%	89.35%	92.52%	90.55%	90.10%	92.05%	89.19%	90.52%	92.15%
150000	92.52%	91.01%	91.72%	91.32%	90.59%	91.10%	91.19%	90.15%	91.70%



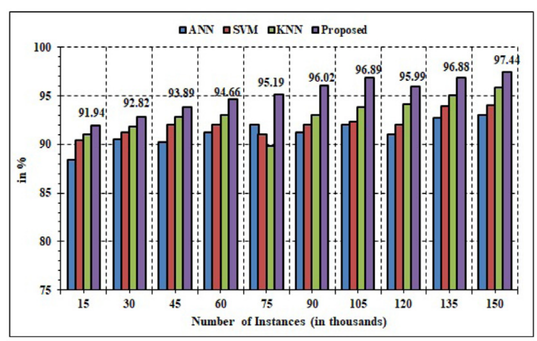
(a) Accuracy



(b) Precision



(c) Sensitivity



(d) Specificity

Fig. 11. Prediction efficiency.

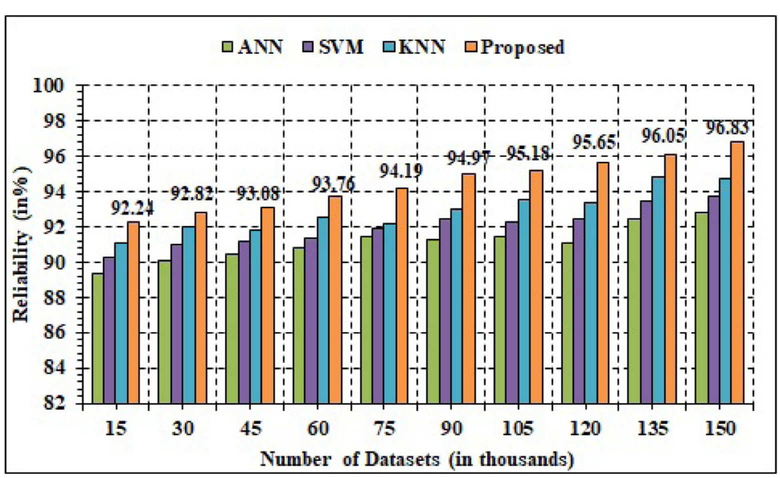


Fig. 12. Reliability analysis.

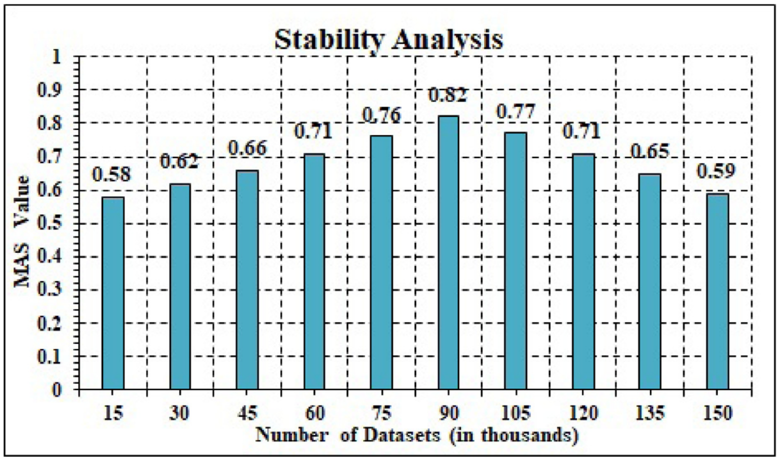


Fig. 13. Overall system stability.

Table 11
Training parameters of ANFIS.

Structure	Value
Inputs	4
Fuzzy Rule	9
Membership Function	Gaussian
Number of Layers	6
Output	1
Reaching Epochs Number	49
Learning Rules	Hybrid

4.7. Stability efficacy

The proposed model is tested for lifespan over time using stability analysis. In other words, when the system is deployed over large datasets for long-term evaluation, the system's stability forecasts overall stabilization. The stability of a system is measured using the Mean Absolute Shift (MAS). The MAS rating falls between 0 and 1, with 0 indicating minimal stability and 1 indicating greatest stability. Fig. 13 depicts the results of the suggested system's stability analysis. It has been determined that the proposed model can register a minimum value of 0.58 and a maximum value of 0.81, resulting in an average value of 0.73. The suggested approach is very stable and suitable for earthquake identification.

4.8. Computational complexity

It is necessary to calculate the system's cost to assess the suggested solution's decision-making efficacy. In this method, two sorts of expenses are estimated: transaction costs and computation costs. Computation cost is the time it takes the system to make a judgment on an event recorded at a certain time instance δT. The cost of a transaction specifies the difficulty associated with the production and authentication of network blocks. The computed complexity is shown in Table 13.

Table 13 illustrates the computing cost of the data collection, preprocessing, and event detection processes. The transaction cost, on the other hand, combines the procedure of key and signcrypted message delivery with the expense of consensus.

5. Conclusion

Earthquake prediction is a complicated branch of study in which the intensity of a future catastrophe is forecasted. Conspicuously, a combination of IoT technology and edge–cloud computing is utilized to monitor and predict earthquakes more efficiently and accurately. The proposed IoT–edge–cloud-based system provides an effective method for prediction along with the transmission of data to the remote cloud server. In the proposed model, seismological data is collected with location information. The edge layer functions as an entry point for the prediction framework which extracts useful features and classifies events based on real-time data. Moreover, cloud computing is used to store and compile data for the prediction of earthquake magnitude. The implementation results demonstrate that the BBM classification technique has superior efficiency and precision at the edge layer level. Compared to state-of-the-art classifier models, the BBM classifier's prediction accuracy of 92.52% is the maximum. Moreover, the performance of the proposed framework is measured in terms of reaction latency, and computational delay, in which optimal results were registered. Conclusively, the presented technique is extremely effective and efficient in provisioning an appropriate earthquake prediction system. For future research, edge layer considerations including sensor energy efficiency, and resource usage can be examined. Security is another vital aspect of future research exploration.

CRediT authorship contribution statement

Munish Bhatia: Conceptualization, Methodology, Software. **Tariq Ahamed Ahanger:** Data curation, Writing – original draft. **Ankush Manocha:** Visualization, Investigation.

Declaration of competing interest

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

Table 12
ANFIS model performance analysis.

Epoch	Training dataset	Training dataset	Training dataset	Testing dataset	Testing dataset	Testing dataset
	R2	RMSE	MAE	R2	RMSE	MAE
25	0.911	0.700	0.814	0.725	0.571	0.763
35	0.957	0.801	0.848	0.741	0.630	0.770
45	0.912	0.805	0.772	0.80	0.711	0.776
55	0.901	0.892	0.783	0.807	0.804	0.784

Table 13
Computational complexity.

Sr. No.	Cost type	Complexity
1.	Computation cost	O(N $\log_n$)
2.	Transactional cost	O(N-1 $\log_n$)

Data availability

The authors do not have permission to share data.

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