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Review

Employing Machine Learning and IoT for Earthquake Early Warning System in Smart Cities

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Abstract: An earthquake early warning system (EEWS) should be included in smart cities to preserve human lives by providing a reliable and efficient disaster management system. This system can alter how different entities communicate with one another using an Internet of Things (IoT) network where observed data are handled based on machine learning (ML) technology. On one hand, IoT is employed in observing the different measures of EEWS entities. On the other hand, ML can be exploited to analyze these measures to reach the best action to be taken for disaster management and risk mitigation in smart cities. This paper provides a survey on the different aspects required for that EEWS. First, the IoT system is generally discussed to provide the role it can play for EEWS. Second, ML models are classified into linear and non-linear ones. Third, the evaluation metrics of ML models are addressed by focusing on seismology. Fourth, this paper exhibits a taxonomy that includes the emerging ML and IoT efforts for EEWS. Fifth, it proposes a generic EEWS architecture based on IoT and ML. Finally, the paper addresses the application of ML for earthquake parameters' observations leading to an efficient EEWS.

Keywords: machine learning; Internet of Things; earthquake early warning system; smart city management; disaster management

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1. Introduction

Recently, several classical and modern technologies have been significantly involved in early warning systems (EWS) [1,2]. Accordingly, efficient integration between the different sciences is desired to serve such important systems. Generally speaking, in the field of seismology, the exerted efforts in risk mitigation, seismic hazard assessment, site specification parameter determination, etc. can contribute in this regard [3–5]. Establishing an efficient earthquake EWS has many concerns that are affected by the day-to-day challenges of earthquake disasters such as the environment type and earthquake parameter observation [6,7].

From the point of view of modern technology, many research attempts have been made to mitigate earthquakes consequences using satellite systems, the Internet of Things (IoT), radio-frequency identification, software-defined network (SDN), 5G, network functions virtualization (NFV), data networks, and other technologies [8–12]. Moreover, using robots along with IoT can represent a remarkable transition in this regard. A unique integrated system called robot-event that can perform automatic inspection and emergency reactions in the case of a large earthquake was proposed by [13]. The wireless communications technology included in the home's seismic warning receiving equipment will send a message to the robot as soon as it detects an alarm. The robot will next start inspecting the inside space using real-time picture tracking and identification. It will travel toward any fallen humans it finds and controls their motions using the robot operating system monitoring interface. The robot is intended to function in a home that has had tolerable damage but is still structurally sound, where furniture may be falling and may endanger the people. The purpose of the indoor experiment was to confirm that the robot system and operation were as intended. The smart robot was developed to work with an intelligent earthquake EWS.

Furthermore, social media played a minor influence in earthquake catastrophe risk mitigation. In [14], the authors proposed employing complete solutions that combined the force of social media with classical ways to mitigate catastrophe repercussions. In the literature context, the research efforts did not stop with remote sensing applications enabled by satellite communication systems [15,16] but also included SDN and NFV, which included IoT-based gateways and Micro-Electro-Mechanical systems (MEMS) nodes [17–20]. That work attempted to assist large-scale domains whose infrastructures had been partially or completely destroyed. Virtualization may also help with catastrophe risk mitigation as a pivot. Such networks need to efficiently preserve the nodes' lifetime, as studied in [21]. In [22], the authors depicted a disastrous scenario illustrating an EWS for a safe plan of evacuation against catastrophe risks by integrating a cloud system-based IoT and heterogeneous network. In the same regard, merging IoT and modern communication technologies and methodologies can also play a key role in smooth and secured data transmission [23–27].

All of these efforts are presented in conjunction with classic earthquake detection and research techniques, as well as fault rupture nature differentiating methodologies, which have been widely investigated in the literature [28]. In [29], a local similarity earthquake detection method based on the notion of the nearest neighbor methodology was suggested for use in assessing the received signal consistency between the studied nearest neighbors among the targeted stations and their closest neighbors. Moreover, [30,31] concentrated on estimating the amplitude of the earthquake from a few early seconds rather than the entire rupture. Meanwhile, the time limitation still necessitates further efforts and research, calculating the earthquake parameters using conventional means takes a lengthy time [32]. The depth and size of an earthquake occurrence may be accurately predicted, as studied in [33]. That model was built on a graph CNN with batch normalization and attention mechanism approaches, for any number of seismic sensors in any location. The performance of four non-linear machine learning models—Random Forest, Gradient Boosting, SVMs, and K-Nearest Neighbors—as well as linear least square regression (LSR) was examined by [34]. They also looked at how well the models calibrated for one region might be applied to another.

The flowing earthquake waves and the complex Earth structure keep the door open for adjustable and intelligent solutions in the study. Modern technology can undoubtedly help to mitigate the earthquake calamity and its implications in this area. ML, for example, is one of the latest technologies that play an important role in tackling complicated issues that lack a specific mathematical method [35]. ML is also a valuable technique for data mining and reassembling missing regular or irregular data. ML algorithms have been suggested in [36,37] to estimate the peak particle velocity (PPV) and to discriminate the quarry blasts. ML has also been used to predict peak ground acceleration and its effect on urban planning [38]. Moreover, microseismic data are among the desired issues that still need more research efforts. In [39], it was suggested to use ML to classify the signal and noise in microseismic data from Pohang, South Korea. While hydraulic stimulation was being carried out, the monitoring system of the borehole station PHBS8 in Yongcheon-ri, Pohang area, for the first time collected distinctive microseismic data. With suitable preprocessing, the acquired data were used as training and test sets for the supervised as well as unsupervised learning algorithms random forest and convolutional neural network besides K-medoids clustering along with fast Fourier transform.

Due to the high scalability of IoT networks and the interconnection of different applications, it has become an inevitable pivot between independent entities such as the ones involved in earthquake early-warning system (EEWS). Moreover, ML can be used for analyzing different data formats and solving complex problems. Accordingly, employing an intelligent system relying on IoT systems in monitoring and ML for efficient data analysis can be a reliable and adaptive solution for EEWS. To achieve such a robust integrated system, several aspects should be accurately investigated such as the IoT devices, environment type, data sources, and ML models. Moreover, the effectiveness of the utilized model is always questionable. Therefore, the validation parameters and their metrics are case-dependent. Table 1 lists the utilized abbreviations throughout the paper.

Table 1. List of abbreviations.

Abbreviation	Description	Abbreviation	Description
EEWS	Earthquake Early Warning System	LSVM	Linear Support Vector Machine
ML	Machine Learning	GNB	Gaussian Naive Bayes
IoT	Internet of Things	AB	Adaboost
SDN	Software Defined Networking	GB	Gradient Boosting
NFV	Network Functions Virtualization	LGB	Light Gradient Boosting
MEMS	Micro-Electro-Mechanical Systems	XGB	Extreme Gradient Boosting
CNN	Convolutional Neural Network	DT	Decision Tree
RF	Random Forest	ET	Extra Trees
SVM	Support Vector Machine	ROC	Receiver Operating Characteristic
SVR	Support Vector Regression	VEO	Volcano Event Ontology
KNN	K-Nearest Neighboring	IRIS	Incorporated Research Institutions for Seismology
LSR	Least Square Regression	STEAD	Stanford Earthquake Dataset
PPV	Peak Particle Velocity	MSE	Mean Square Error
NIED	National Research Institute of Earth Science and Disaster Prevention	Std	Standard Division
AE	Autoencoder	UAV	Unmanned Aerial Vehicle
FL	Federated Learning	NOAA	National Geophysical Data Center
PGA	Peak Ground Acceleration	JMA	Japan Meteorological Agency
DMSEEW	Distributed Multi-Sensor Earthquake Early Warning	GSI	Geological Survey of India
GPS	Global Positioning System	USGS	United States Geological Survey
LR	Linear Regression	ANN	Artificial Neural Network
LDA	Linear Discriminant Analysis	CRNN	Convolutional-recurrent neural network
QDA	Quadratic Discriminant Analysis	MLP	Multilayer perceptron

In the literature context, the exerted efforts only focused on a general overview for the integration of different technologies such as IoT, ML, etc. for EEWS [6,11,20,40,41]. Such efforts concentrated on seismic alert systems. Unlike previous work, we propose a comprehensive paradigm for an effective EEWS throughout two phases. The process involves two stages. The ML models are used in the first stage, which is the pre-disaster phase, to identify the beginning of the primary wave. For risk mitigation, such an EEWS is useful for fast switching off to nuclear plants, electricity generators, etc. Following the disaster presence, the second phase starts to alleviate the earthquake consequences. This system efficiently integrates ML and IoT supported by an informative taxonomy to achieve a practical robust EEWS.

To the best of our knowledge, the introduced taxonomy of the integrated system based on ML and IoT has not been considered in the literature. More particularly, in this paper, we investigate the essential roles of ML and IoT as key technologies to attain an effective EEWS in smart cities. More particularly, preserving human lives in smart cities against earthquake disasters cannot be achieved without a reliable EEWS. In this regard, we have presented a general overview of the IoT systems showing their system framework and statistical forecasting of IoT usage. Afterward, we generally classified the ML models into linear and non-linear approaches as well as the evaluation metrics of the main ML models developed for seismology. Then, we present the exerted efforts of the IoT and ML integration for EEWS supported by a comprehensive taxonomy concerning the ML models, IoT devices, environment type, data source, measured parameters, and validation metric. Moreover, we portray a general architecture using IoT that integrates the potential administrations in case of a disaster.

The major contributions of the paper highlighting the innovation points are as follows.

- We shed light on the desirability of the EEWS for smart cities.
- As IoT and ML are among the key technologies involved in the EEWS, we highlight the development of IoT usage including the general IoT system framework and its components.
- The ML models are generally classified into linear and non-linear approaches.
- The main evaluation metrics of ML models dedicated to seismology are addressed.
- A thorough taxonomy of ML models, IoT devices, environment type, data source, measured parameter, and validation metric is presented to demonstrate the efforts made to integrate IoT and ML for EEWS.
- Finally, we illustrate a general IoT architecture that combines the potential disaster administrations.

The rest of the paper is organized as follows. Section 2 portrays an overview of IoT systems. Section 3 presents an ML taxonomy. Section 4 addresses the commonly involved metrics used to evaluate the ML models. The integration of IoT and ML for EEWS is illustrated in Section 5. Then, a general EEWS is presented in Section 6. Section 7 introduces open applications of ML in seismology to the stakeholders, and finally, the paper is concluded in Section 8.

2. Internet of Things (IoT) Systems

IoT is becoming more extensively embraced globally as a new technology. Table 2 shows the growth of smart technology according to Gartner research [42]. A network of connected embedded items or devices with identifiers that can communicate using a standard communication protocol without human intervention is referred to as an IoT [43–46]. According to reports, there are already more internet-connected devices than people on the planet, and these IoT devices serve as the foundation for smart cities [47–49]. As demonstrated, there will be a significant number of smart residences and commercial structures where smart power and water management are crucial requirements to be addressed. From 9.7 billion IoT devices in 2020 to more than 29 billion IoT devices in 2030, the number of IoT devices is expected to nearly treble [42]. China will have almost 5 billion consumer IoT devices by 2030, making it the country with the most of them. Consumer markets and other business verticals both employ IoT devices, with the consumer market expected to account for over 60% of all IoT-connected devices by 2020. Over the following ten years, it is expected that this share will remain at this level.

Table 2. Number of Internet of Things (IoT) connected devices worldwide from 2019 to 2021, with forecasts from 2022 to 2030. These statistics are extracted from [42].

Year	2019	2020	2021	2022 *	2023 *	2024 *	2025 *	2026 *	2027 *	2028 *	2029 *	2030 *
Connected devices in billions	8.6	9.7	11.3	13.1	15.1	17.1	19.1	21.1	23.1	25.2	27.3	29.4

* Refers to statistical forecasting.

Electricity, gas, steam, air conditioning, water supply, waste management, retail and wholesale, transportation and storage, and government are major industry verticals with more than 100 million linked IoT devices at this time [50–52]. By 2030, there will be more than eight billion IoT devices in use across all industry verticals. Consumer internet and media devices such as smartphones, where the number of IoT devices is expected to increase to more than 17 billion by 2030, represent the most significant use case for IoT devices in the consumer market. By 2030, linked (autonomous) vehicles, IT infrastructure, asset tracking and monitoring, and smart grid will all have more than one billion IoT devices in use [53–55].

According to accepted standards [56–60], the following steps should be taken while setting up an IoT system:

- The device with the data-gathering capability of the environment (including the identification address of the sensor).
- A tool for gathering and analyzing data so that knowledge can be drawn from it.
- Making decisions and sending information to the required hubs. Big data analytics and actuators are utilized for the same purposes.

The general structure of an IoT solution is realized based on the research conducted on the various IoT systems. A typical IoT system's structure or architecture is shown in Figure 1. A sensor network that monitors environmental changes makes up an IoT system. Depending on the desired distance and data speed, these measured data must be sent to a central or decentralized system via connectivity such as 3G, Bluetooth, Zigbee, etc. The sensor system also requires a consistent power source. The power capacity mostly depends on the connectivity, as systems such as 3G use more power than Bluetooth; therefore, this should be taken into consideration when selecting connectivity. Additionally, care must be taken with the hardware and connectivity's security aspects. The primary requirement for an IoT system is that the solution is usable by everyone, not just a specialist. The data received in the cloud system are analyzed or stored in order to find patterns and to extrapolate knowledge. Data visualization can be carried out to make it simpler for the user to grasp, and alert systems can be used to send the right kind of warning.

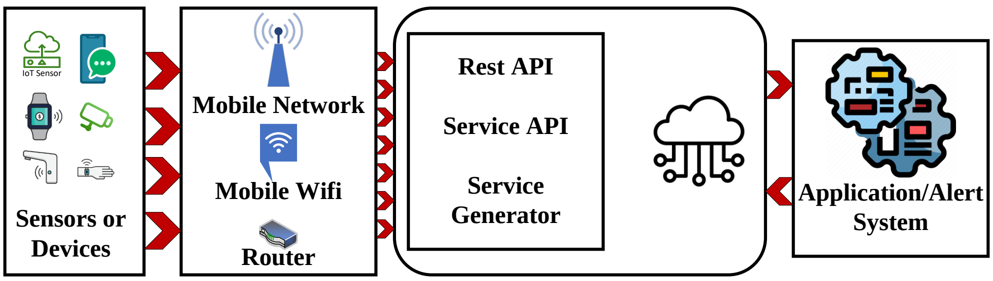

Figure 1. IoT system framework.

3. Machine Learning Taxonomy

Ordinarily, a human is required to investigate data and to determine an object's classification. Using appropriate ML algorithms, the goal is to make this operation as automated as possible. In this section, we categorize the main developed ML algorithms in the literature. Following is a brief explanation of each method of operation. To put it another way, we create a categorization of the most frequent linear and nonlinear ML approaches used in the literature, as depicted in Figure 2. It is worth mentioning that linear ML algorithms assume a linear relationship between the features and the target variable.

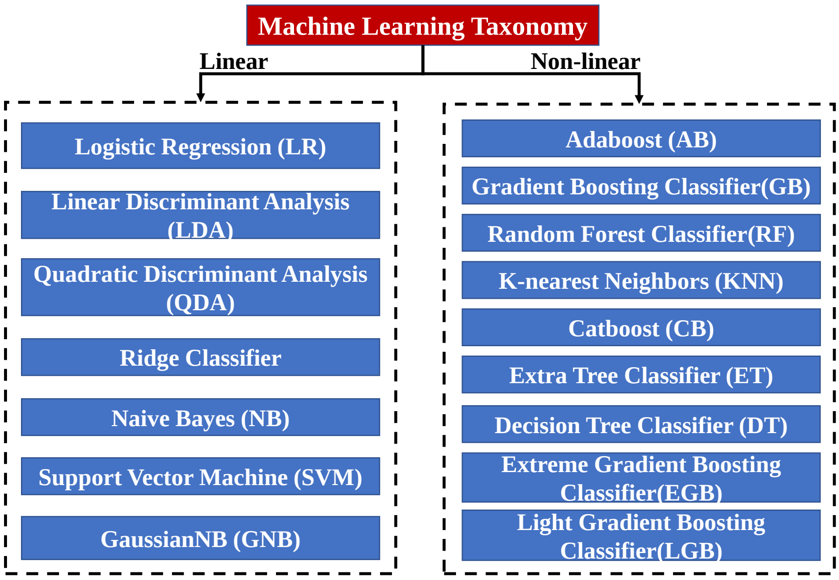

Figure 2. ML taxonomy.

3.1. Linear Approaches

3.1.1. Logistic Regression

In the statistical study of a dataset containing numerous independent variables, logistic regression (LR) is used to arrive at a binary conclusion. LR approaches the likelihood feature classes (K) to fit data across a logit function that yields a binary output $\in \{0,1\}$. Multinomial LR is used to classify situations with more than two outcomes. The initial step is to categorize the inputs as either class 0 or class 1. The probability tends to class 1 is addressed by the LR. The probabilities are then classified using a logit function to discriminate the components into the two targets $\in \{0,1\}$. Following that, LR establishes a distinction level for values $\in [0,1]$ [61].

3.1.2. Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA)

Linear Discriminant Analysis (LDA) was created to address many challenges that the LR faces. The LR is not suited for parameter assessment when the classes are sufficiently divided. The LDA model, on the other hand, is more suitable than the LR when a short sample length is used and each class contains a normal distribution of predictors. Before using the LDA, it is necessary to consider a hypothesis for the processed data where the normal distribution is used for each predictor. However, when it is easy to describe the data (higher or lower than a linear hypothesis), the LDA may be insufficient. In these instances, the Quadratic Discriminant Analysis (QDA), which relies on a non-linear assumption, is also suitable [62].

3.1.3. Linear Support Vector Machine (SVM)

The SVM aims to discover an ideal hyperplane taking into account K features. In order to obtain the optimum intended hyperplane, the input data features are addressed for a K-dimension space. The hyperplane can be realized if the distances among the data points are maximized. For depicting the data points close to the hyperplane besides influencing the hyperplane behavior, SVMs can be utilized. Moreover, another enhanced version of SVM, namely linear SVM (LSVM), was proposed to offer attributes between $[-1, 1]$, which is sent to the output of a linear function like the LR. It is important to note that the use of the SVM stabilizes boundary maximization and boundary loss depending on a cost function regularization parameter. The aforementioned process is considered to aim at maximizing the boundary among the hyperplane and data points [63,64].

3.1.4. Ridge

It is commonly used for the regression problem, mapping label data in the range of $[-1, 1]$. As a result, it employs a regression mindset to tackle the problem. The highest prediction value is translated to the target class after that, although in the event of multiclass data, multi-output regression is used [65,66].

3.1.5. Naive Bayes (NB)

The NB is broadly nonlinear. The NB classifier in contrast is handled as a linear approach if the likelihood factors rely on exponential sets. A Gaussian paradigm is a variant of the NB method (GNB) that is used in the situation of continuous value features. Specifically, the features are expected to follow a Gaussian distribution supervised by [67]. The GNB is a likelihood classification approach. The likelihood is given by the following:

$$p(d = F|C) = \frac{1}{\sqrt{2\pi\sigma^2}} \times e^{-\frac{(F-\mu)^2}{2\sigma^2}} \quad (1)$$

where the continuous data input is represented by d, the probability density is denoted as F , the class is constituted by C , the variance is represented by σ, and the mean is μ.

3.2. Non-Linear Approaches

3.2.1. AdaBoost (AB)

The AB uses adjustable boosting to stratify successive soft classifiers to improve datasets by aggregating them into a stronger discriminator relying on the majority of a weighted vote. The AB method gives higher weights to items that are difficult to discriminate and lower weights to those that are simple to classify. This approach starts the censorship weights [68] in the first stage. Then, the approach is fitted based on the weights, and the error rate is calculated, after which another weight is given to the approach to discriminate the classifier's conclusion. The new discriminator is then compared to the previous classifier to see if the new tree can make a better prediction. As a result, the resulting model is a hybrid of the two trees. This technique is repeated indefinitely for specified epochs [69].

3.2.2. Gradient Boosting (GB), Light Gradient Boosting (LGB), and Extreme Gradient Boosting (XGB)

To begin, the GB converts soft discriminators to more robust ones. It uses a gradient to determine the soft discriminators' weaknesses. Furthermore, GB's loss function employs high-weight data points. As a result, GB allows for a common and stated cost function for optimization. Accordingly, it is acceptable for discrimination [69]. The LGB is a modified version of the GB. To put it another way, LGB is being developed as a more effective distributed approach than GB [70]. The XGB is a more streamlined paradigm of the GB that offers increased efficiency, versatility, and likelihood. It offers a fast accurate parallel tree boosting [71]. Furthermore, using the apportionment of characteristics for leaf data points, the XGB examines the probable loss for probable divisions to form a new division. This strategy is employed to reduce the search span for prospective feature divisions. For optimal tuning, this approach uses a large number of hyper-parameters.

3.2.3. Random Forest (RF), Decision Tree (DT), and Extra Trees (ET)

To begin with, RF is one of the ensemble approaches based on the tree notion. It is made up of parallel learners utilized to reduce prejudice and variation at the same time [72]. In general, RF is used in classification issues as a probabilistic estimator:

$$\hat{D}(\mathbf{v}) = \frac{1}{T}\sum_{j=1}^{T} R_j(\mathbf{v}), \tag{2}$$

where $\mathbf{v}$ expresses the input vector, T is the trees' number, and $R_i(\mathbf{x})$ denotes regression tree (j^{th}).

The ET approach is a variant of the RF, with a lower likelihood of overfitting. It can select the best features from the input data at random to help the investigators attain efficient results [73]. The DT approach is excellent for both discrimination and regression issues and is capable of splitting large problems into several simpler ones in order to facilitate solution fulfillment [74,75].

3.2.4. *K*-Nearest Neighbors (KNN)

The KNN mechanism is a discrimination approach that relies on the decision-boundary for classifying an input. Its strategy is based on the majority of the nearest neighbors' class [76]. Both The involved neighbors set and the distance factor of the nearest neighbors are configurable hyperparameters for this algorithm. Due to KNN being vulnerable to excessive dependency on noise or outliers, the smallest KNN is attained at $k = 1$. Furthermore, KNN variations can evaluate the training-set votes based on the cosine analogy to the input.

3.2.5. CatBoost (CB)

The CB is based on insensible trees that are considered a depth-first expansion. In detail, CB employs a vectorized tree impersonation, with each level employing a binary splitting approach. As a result, it yields a fast convergence. Conversely, CB is not recommended for use with low false-positive rates, according to [77]. The following section discusses the metrics involved in evaluating common ML models focusing on the ones utilized in seismology.

4. Evaluation Metrics of ML Models

In the literature context, several metrics can be used to evaluate the model performance. The commonly known one is the accuracy score which is calculated by the ratio of the correct predictions to the total number of estimations:

$$\text{Accuracy} = \frac{\sum_{j=1}^{N} I(\hat{y}_j = y_j)}{N} \tag{3}$$

where N expresses the total number of estimators, $\hat{y}_j$ is the predicted target, the true label is y_j, and I denotes the indicator function. It is worth mentioning that the predicted labels fully match the true ones when the optimal score of accuracy is 1. This metric has been widely used in seismology such as in [78,79]. The authors have utilized their models for efficient acceleration data observation and for determining its quality by computing the noise levels. Moreover, the metric has been employed for evaluating the model of earthquake detection. However, this metric cannot handle the class imbalance problem.

A different evaluation metric is the Cohen Kappa score (κ), which relies on random predictions. The κ determines how well the discriminator precisely acts, where its optimum score is 1. This score is derived by the following [80]:

$$\kappa = \frac{\text{TA} - \text{EA}}{1 - \text{EA}}. \tag{4}$$

where TA is the true accuracy and EA is the estimated accuracy. This metric has been used for ensuring the discrimination efficiency of earthquakes and quarry blasts [1], but the expectation of its values is difficult.

In addition, discrimination evaluation can be measured by precision and recall, and F1-score factors, which are given by the following:

$$\text{Precision} = \frac{TP}{TP + FP}, \tag{5}$$

$$\text{Recall} = \frac{TP}{TP + FN}, \tag{6}$$

$$\text{F1-score} = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \right), \tag{7}$$

where the true positive decision is represented by TP, the false positive decision is represented by FP, while a false negative decision is denoted by FN. In many cases of measuring the models' accuracy, the F1-score has been adopted [81–83]. These metrics have been employed for evaluating models of differentiation between earthquakes and artificial seismic sources and for identifying exposure of the urban area to certain seismic hazards. However, it does not consider the true negatives.

Moreover, the receiver operating characteristic (ROC) curve represents another graphic we can make with these prediction results. The graphs of the classifier's targets $\in \{0, 1\}$, micro-average, and macro-average indicate the relationship between the TP rate and the FP rate. The accuracy of the classifier improves as the TP rate approaches 1. The classifier efficiency is determined by estimating the label targets as the percentage of samples varies by charting the cumulative profit of the label objectives relating to the sample percentage [84]. Indeed, ROC has proved beneficial in measuring earthquakes compared to quarry blast discrimination model effectiveness [37], earthquake detection, and noise discrimination. However, in ROC, the FP and FN analyses have different misclassification values.

Moreover, R^2, root-mean-square error (RMSE), and MSE are used for models' evaluation. First, in statistics, the determination coefficient, denoted by R^2 and pronounced "R squared", is the variation proportion in the dependent variable predicted from the independent variable(s). This scoring value can be computed by the following:

$$R^2 = 1 - \frac{RSS}{TSS}, \tag{8}$$

where the sum of squares of residuals is represented by RSS and the total sum of squares is denoted as TSS, which can be given by the following:

$$RSS = \sum_{i=1}^{z} \left(y_i - f(x_i)\right)^2, \tag{9}$$

$$TSS = \sum_{i=1}^{z} \left(y_i - \hat{y}\right)^2, \tag{10}$$

where the number of observations is denoted as z, the i^{th} value to be predicted is represented by y_i, the predicted value is $f(x_i)$, and the sample mean value is $\hat{y}$.

Second, the RMSE/MSE is the most commonly utilized loss function measure in the assessment process. The MSE can be given by the following:

$$MSE = \frac{1}{N} ||\mathbf{V}_T - \mathbf{V}_P||, \tag{11}$$

where the set of true values is denoted as $\mathbf{V}_T$, the Euclidean norm is represented by $||.||$, and $\mathbf{V}_P$ represents the predicted values set that can be given as follows:

$$\mathbf{V}_P = f(\mathbf{X};\theta), \tag{12}$$

where the parameters that contain the sets of weights and bias values represented by **W** and **b**, respectively, are represented by θ. Additionally, the probability density function of the predicted values can be given by the following:

$$f(v) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(v-\mu)^2}{2\sigma^2}}, v \in \mathbf{V}, \tag{13}$$

where the test set used for the prediction process is denoted as $\mathbf{V}$. R^2, MSE, and RMSE, have been utilized for several applications in seismology such as PPV estimation, location, and magnitude detection and prediction, etc. [31,36]. On the other hand, they have some drawbacks such as the inability to calculate predictive error and the high probability of having outliers.

5. IoT-ML Integration for EEWS

This section presents the significant roles of both IoT and ML in EEWS. Furthermore, it investigates previous work that aimed at predicting the earthquake parameters via ML models. Moreover, these models have been integrated with IoT technology to serve EEWS in a reliable manner. Indeed, the integration of IoT and ML have proved beneficial for EEWS enhancements in both pre-disaster and post disaster management.

In [85], mobile computing, remote sensing, SVM, and KNN ML models have all been employed to alleviate the effects of earthquake disasters. Entity categories, geographical linkages, and entity names serve as input features to the ML models used in this model, which is assessed using the accuracy measure. In [78], the authors proposed a seismic detection system relying on deep learning, namely CrowdQuake, to utilize a dense IoT network for analyzing the big deal of observed acceleration data via multi-head convolution neural network. The IoT network employed the MEMS nodes. The model is examined by evaluating the noise level in the signals as well as the accuracy, and precision-recall. In that work, the data were collected from the National Research Institute of Earth Science and Disaster Prevention (NIED). The authors mentioned that the developed model could deal handle data sent from 8000 IoT sensors and only a few seconds were needed to detect an earthquake. In [79], a robust EEWS has been developed based on real-time alerts supported by an IoT network. The network adopted the MEMS accelerometers with Arduino Cortex M4 microcontroller. That system employed ML for earthquake detection accuracy as well as detection latency. That model relied on locally collected acceleration data via the deployed MEMS accelerometer nodes.

In [86], the IoT acceleration nodes have been developed to detect earthquakes. In that work, there are two methods for using such devices as seismic sensors: a standalone method or a client-server method. The client-server method is more precise than the stand-alone method, but it necessitates high-performance servers as well as network infrastructures. This handles the data acceleration gathered from several client machines. Simple earthquake detection paradigms can be readily considered in a standalone way on less capable mobile nodes, but there exists a chance of false warnings. This limitation is overcome via a cooperative technique that makes use of several adjacent mobile phones to detect an earthquake, improving the earthquake detection capability of the standalone solution without system and network infrastructures. The nearby cellphones build a seismic network to jointly detect earthquakes, and they then watch for any shaking brought on by human activity, mechanical vibrations, earthquakes, etc. Using an earthquake detection method relying on a key neural network, a smartphone that detects an earthquake-like motion communicates the detection result to other cellphones nearby in a multi-hop fashion. Each smartphone involved in the seismic network undertakes a decision-making operation after receiving the detection data from adjacent smartphones, reports an earthquake, and then initiates an alarm.

In [87], the geological landslide events have been monitored by exploiting a predictive model employing both IoT devices and an ML scheme. Data from numerous geotechnical factors, such as soil moisture, soil shear strength, rain intensity, terrain slope, etc., were used to train the prediction model. A collection of sensors makes up the hardware, which collects the necessary soil and terrain characteristics in real-time. The authors in [88] suggest a compute offloading system design for Internet-connected drones. The performance of the edge computing technique vs. the cloud compute offloading approach for deep learning applications (CNN) in the context of UAVs is then assessed through a thorough experimental analysis. The authors specifically conduct an experimental investigation of the trade-off between the communication cost and the computation of the two possible methodologies.

For an instant discovery of earthquake magnitude and position after 3 s from the start of the P-wave, a deep learning paradigm based on integrating an autoencoder (AE) and a convolutional neural network (CNN) was proposed in [31]. The authors thus call it 3 s AE and CNN (3S-AE-CNN). Three stations from the Japanese Hi-net seismic network monitor the used data set. The approach has been practiced on 12,200 events (109.80 thousand 3 s three-component seismic windows). The model makes it easier to extract the important characteristics of waveforms, which results in a reliable assessment of the earthquake parameters. The suggested model's magnitude, latitude, and longitude predictions are accurate to within 0.000028, 0.0000033, and 0.0001 degrees, respectively. The suggested 3S-AE-CNN model quickly transmits the earthquake's characteristics to a centralized IoT system, which then instructs the concerned organization to take the appropriate action.

A brand-new framework for predicting earthquakes based on federated learning (FL) has been released [89]. The suggested FL framework beat previously created ML-based earthquake prediction models in terms of efficiency, dependability, and accuracy. We have investigated three different local datasets to build multiple ML-based local data models. These local data models have been integrated using the FedQuake algorithm on the central FL server via an IoT gateway to create global data models. That model analyzed multidimensional data over 100 km radial area aside Western Himalayas achieving an accuracy of 88%. In [81], it has been suggested to use an IoT-based warning system with a machine learning classification algorithm to anticipate tsunamis. The model was trained using historical tsunami data drawn from records dating back to 2100 BC. Based on the dataset's earthquake parameters, that model has been trained based on location, depth, and magnitude, reaching an accuracy of 95%.

A deep learning algorithm that can find P-waves in noisy situations has been developed by [82]. The model exploited the MEMS nodes for events observation. The model produces the likelihood of discovery before the onset of strong shocks. That model could achieve an accuracy of 98.8% of P-waves within 1.5–2.5 s from its arrival. To detect earthquakes locally, the authors in [90] suggested bringing computing to the edge and using detector nodes that probe the environment and to analyze data from neighboring probes. The method maintained all data locally while tolerating numerous node failures and partial network disruption, boosting privacy. Indeed, twenty instances of the node code, each operating on a separate machine and connected to ten arbitrary neighbors, were used to construct the test network. In addition, every 10 s, the number of detectors was sampled. By forecasting the likelihood that the onsite intensity would surpass a pre-trained PGA threshold associated with harmful intensities in the MMI scale, a Multilayer Perceptron-classifier was designed to deliver the severity-based warning in [83]. Seismic characteristics that were recovered from the strong-motion signal following the commencement of the p-wave were used in the classifier's supervised learning process. The application of a stratified differential feature-window resampling was adopted.

In [91], the authors presented a standalone earthquake detector with a low-cost acceleration sensor and little computer power. To achieve this, they first evaluated the effectiveness and precision of four distinct acceleration sensors, before choosing the best one. After that, they created an earthquake alarm system. They used a straightforward machine learning approach to identify earthquakes that train an earthquake detection model using daily vibrations, noise data collected from buildings, and previously recorded earthquakes. The four acceleration sensors were further tested by the authors by recording two actual earthquakes on a shake table. That work noted that the low-cost acceleration sensors can monitor changes in acceleration brought on by different degrees of earthquakes ranging from 0.02 g to 0.8 g in order to identify earthquakes. Accordingly, the authors utilized the scaled data within that range.

Instead of using conventional seismic techniques, it made use of an ML methodology with earthquake characteristics [92]. The detection problem was first divided into two groups by the authors: static environments and dynamic environments. Following an experimental evaluation of several features, they recommend the best ML model and features for the static environment in order to address the problem of noisy components and to identify earthquakes in real-time with a lower rate of false alarms. That model has been realized using 385 earthquake events with magnitudes ranging from 4 to 8.

To identify medium and big earthquakes, the authors in [93] presented the Distributed Multi-Sensor Earthquake Early Warning (DMSEEW) system, a cutting-edge ML-based method that incorporates data from both types of sensors (GPS stations and seismometers). The foundation of DMSEEW is a novel stacking ensemble approach that has been tested on a real-world dataset and verified by geoscientists. The system was developed using a geographically dispersed infrastructure, guaranteeing fast computing and resilience to partial infrastructure outages. More particularly, that systems integrated GPS data with seismic data to improve the earthquake detection quality leading to an effective EEWS.

To gather, interpret, and store seismic data into a knowledge base, the authors in [94] presented an IoT-oriented system. A seismic domain ontology dubbed Volcano Event Ontology (VEO) intends to aggregate seismic signals gathered by sensors for seismic event identification. The well-known SSN/SOSA ontology, which is used to represent systems of sensors, actuators, and observations, served as the foundation for the ontology's construction. Monitoring networks at Mt. Vesuvius (Naples, Italy) and Colima volcano (Mexico) have gathered seismic data, which has been aggregated in the ontology. Additionally, a classification module analyzed the seismic data to identify various seismic occurrences (such as volcano-tectonic and long-period earthquakes, underwater explosions, and quarry blasts), after which the information was saved in the knowledge base. The data collection was created by gathering and analyzing seismic data from the volcanoes Colima and Vesuvius. The dataset was composed of 4008 signals in SAC format. The model achieved 93% accuracy examined by F1-score.

Despite extensive efforts exerted in the state-of-the-art methods, an intelligent, reliable, and adaptable solution is strictly desired due to the vulnerability of the targeted problem, and the direct effect on human life. Here, we shed light on the main research explorations in this regard. Table 3 summarizes the main efforts carried out using IoT and Ml for the EEWS.

Table 3. Summary of IoT and ML main efforts for EEWS.

Ref.	ML Model	IoT Device	Environment	Dataset Type	Data Source	Measured Parameter	Validation Metric	Pros of Used ML Model	Cons of Used ML Model
[78]	Multi-head CNN	MEMS	Under ground	Acceleration data	NIED	Acceleration, SNR	Accuracy, and precision-recall	Very high accuracy in image recognition	Do not encode the position and orientation of object

Table 3. *Cont.*

Ref.	ML Model	IoT Device	Environment	Dataset Type	Data Source	Measured Parameter	Validation Metric	Pros of Used ML Model	Cons of Used ML Model
[79]	Simple ML model	Arduino Cortex M4 microcontroller	Underground	Acceleration data	Local data observed by MEMS accelerometers	earthquake detection accuracy and detection latency	Accuracy	Easy to implement	Poor performance on non-linear data, high reliance on proper presentation of data
[85]	SVM and KNN	remote sensing-based mobile computing	Indoor	GIS data	Open Street Map, Wikimapia, and Google places	Affected areas via maps	Accuracy	For SVM: Performs well in Higher dimension, best algorithm when classes are separable. For KNN: No Training Period, easy Implementation	For SVM: Slow, poor performance with Overlapped classes. For KNN: does not work well with large dataset, does not work well with high dimensionality
[86]	basic neural network	IoT acceleration nodes	Indoor non-line-of-sight	Acceleration data	Local distributed smartphones	PGA and human activity	Accuracy, precision-recall, F1	Easy to implement	Poor performance on non-linear data, high reliance on proper presentation of data
[87]	SVR and XGB	IoT soil and terrain nodes	Underground	Soil moisture, shear strength of the soil, severity of the rain	GSI	Soil moisture, Soil shear strength , rain severity	Std and accuracy	Outliers have less impact, suited for extreme case binary classification. For XGB: Effective with large data sets	Needs appropriate hyperparameters, selecting the appropriate kernel function can be tricky. For XGB: Can over-fit with noisy data

Table 3. *Cont.*

Ref.	ML Model	IoT Device	Environment	Dataset Type	Data Source	Measured Parameter	Validation Metric	Pros of Used ML Model	Cons of Used ML Model
[88]	CNN	UAV-based IoT	Outdoor line-of-sight	Aerial images data	Local drones	Received frames/sec	Throughput	Automatically detects the important features	Lack of ability to be spatially invariant to the input data
[31]	AU and CNN	Tmote Sky	Indoor and Outdoor	Seismic velocity data	JMA and Hi-net	Location and magnitude	MSE and Std	Weight sharing	Lots of training data is required
[89]	FL	IoT gateway	Underground	Seismic waveform	Local datasets and regional data [95]	Earthquake predictions	Accuracy, precision -recall, F1, loss	Learn many models simultaneously, having access to various data	Hard verification, data and model privacy
[81]	RF	Mobile nodes-based feed processor	Over the coastal regions	Tsunamic data	NOAA	Location, depth, and magnitude	Confusion matrix, accuracy, precision-recall, F1	No scaling required	Extensive computations
[82]	CNN and LSTM	MEMS	Noisy environments	Seismic waveform	STEAD	P-wave arrival	Accuracy, precision-recall, F1	Low weight complexity	Require a lot of resources and time, affected by different random weight initialization
[90]	CRNN	Raspberry Pi	Mesh network	Seismic waveform	Locally observed	Local earthquake	Accuracy and latency	Generate better or optimal results than either CNN	High complexity, heterogeneity
[83]	MLP	Strong motion nodes	Underground	Acceleration data	NIED	PGA	Precision-recall, F1	Solve complex non-linear problems	High computations
[91]	Simple ANN	Acceleration sensors (ADXL355, LIS3DHH, MPU9250, and MMA8452)	Underground	Accelaration data	NIED and USGS	PGA	Confusion matrix, accuracy, precision-recall, F1	Can work with incomplete knowledge	Unexplained behavior

Table 3. *Cont.*

Ref.	ML Model	IoT Device	Environment	Dataset Type	Data Source	Measured Parameter	Validation Metric	Pros of Used ML Model	Cons of Used ML Model
[92]	Simple ANN	Smartphones	Static and dynamic environment	Acceleration data	NIED and USGS	Earthquake data	Confusion matrix, accuracy, precision-recall, F1	Having fault tolerance	Hardware dependence
[93]	KNN, SVM, RF, XGB	GPS stations and seismometers	Underground	GPS and Seismic velocity data	IRIS and NIED	Earthquake data	Precision-recall	For RF: High accuracy, can handle linear and non-linear relationships	Not easily interpretable
[94]	CNN	SSN/SOSA ontology	Underwater	Volcanic data	Local data	Volcano-Tectonic, long-period earthquakes, underwater explosions, and quarry blasts	Confusion matrix, accuracy	Very high accuracy	Lots of training data is required

6. General Architecture of EEWS Process via IoT and ML

The need for an EEWS is unavoidable to preserve human lives. The ability to quickly determine the characteristics of an earthquake is critical in disaster management and earthquake risk mitigation. To mitigate an earthquake disaster, these characteristics can be sent using current technologies such as the IoT network, mobile network, global positioning system (GPS), and social media.

Figure 3 shows an entire EEWS that involves several administrations contributing to alleviating the earthquake disaster. Based on these administrations, the EEWS will have full statistics about hospitals, railways, fire departments, ambulances, airports, etc. Indeed, this proposed system integrates IoT systems, cloud systems, social networks, different utilities, and cellular networks. The system works in two phases. The first is a pre-disaster stage in which the ML models are involved to pinpoint the primary wave onset. This process is very beneficial for risk mitigation such as fast switching off to nuclear plants, electricity generators, etc. The second phase is after the disaster occurrence where the target is to mitigate/reduce the consequences of the disaster. For example, using such an integrated system facilitates accurate statistics about the afflicted people, buildings, utilities, and areas affected by the disaster. Accordingly, an effective evacuation plan can be executed.

Such a system needs an adaptive and intelligent solution that is capable of resolving complex problems in a short period. Among the span of the existing current methodologies, ML can play a significant key role in those interconnected administrations involved in achieving effective EWS. ML is a promising tool that does not be affected by the data type, format, length, etc.

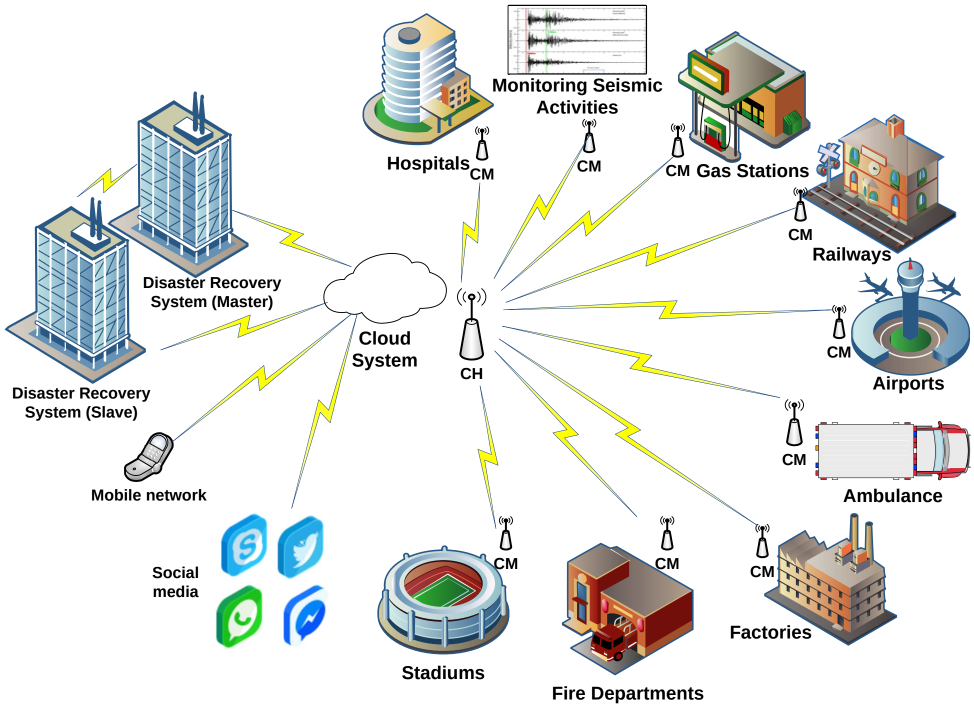

Figure 3. General diagram for a comprehensive EWS.

Indeed, the distributed entities presented in Figure 3 and utilized for achieving a robust EEWS, are monitored as real-time applications. Therefore, data transfer back and forth from these entities should be accurately analyzed and estimated. Hereafter, the ML models are employed in this important role to pinpoint the current status of each entity and to even estimate for a specific period. Afterward, those entities can be efficiently utilized before, during, and after earthquake disasters. In other words, such a process can contribute to earthquake disaster management, risk mitigation, and evacuation plans. Accordingly, the better the ML model developed, the more effective EEWS. Figure 4 indicates the interconnection between railways as a specific entity involved in the entire EEWS process and the data analysis as well as the investigation conducted by ML via the IoT system. More particularly, the seismic activity is observed and then transferred to the data processing stage using an ML model along with the railway information of the disaster location via the IoT system to perform the required analysis and to take the appropriate decision/(s) to be sent back to the railway system for action.

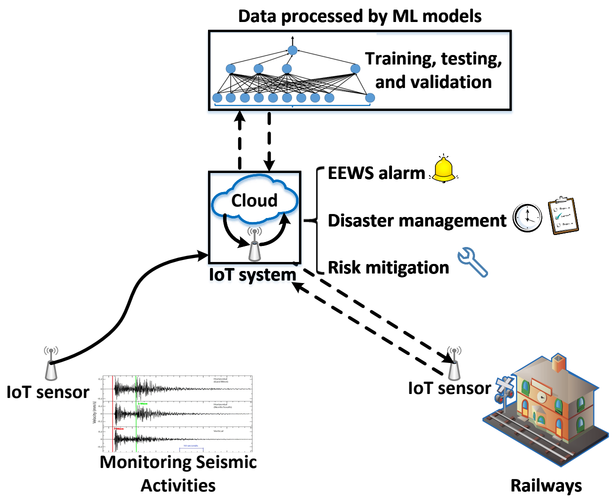

Figure 4. A sample of IoT-ML interconnection for EEWS.

7. Applications of ML for Earthquake Waves

Due to the fast booming of ML and its reliability in solving complex problems, it can provide an effective and adaptive solution for the following open areas of the earthquake field:

- Picking: this means accurately pinpointing the onset of the primary wave that precedes the strong and destructive wave. In this regard, CNN, capsule network, and LSTM have played significant roles, with sufficient accuracies of 98.6%, 97.64%, and 98.8%, as presented in [82,96,97], respectively.
- Denoising: this denotes splitting the real events from the noise wave. Indeed, the noise represents all types of waves except the ones generated from an earthquake. In [98,99], the authors developed a deep denoiser using supervised AE models. The models achieved an accuracy between 85.5 and 98.9%. Another model relied on CNN for denoising by considering the signal-to-noise ratio (SNR) as an indicator of the model performance [100].
- Noise and Microseismic Discrimination: this represents accurate classification between the noise and the real events of very low magnitudes. In [101], an SVM model succeeded in discriminating between noise and microseismic waves with an accuracy of 92% for noise and 95% for microseismic waves.
- Clustering: this distinguishes areas based on the density of earthquakes, earthquakes magnitudes, etc. In [2], the authors utilized affinity propagation methodology for area clustering in which the SNR was employed to evaluate the model. Other efforts used both deep AE and deep scattered network for the same target, as in [102,103].
- Magnitude Estimation: this means determining the observed event magnitude. It is worth mentioning that calculating the magnitude of earthquakes can contribute to the analysis and implications for active tectonic structures [104]. Indeed, AE, CNN, RNN, and SVM proved beneficial in earthquake magnitude estimation. The supervised models have been evaluated using MSE and standard division, as studied in [31,105,106].
- Phase Detection: this provides information about the received signal component, whether primary wave or secondary wave. Phase detection have been studied by some researcher in the literature. In [107], the authors proposed a CNN model that achieved an accuracy of 99.8%. Moreover, general software has been developed based on deep learning, as in [108].
- Peak Ground Acceleration Estimation: this addresses the maximum acceleration that could happen at a specific location. The PGA is an essential parameter that can be used for building codes. In [109], an ensemble learning model was utilized for estimating the PGA parameter, as the model was evaluated by ROC curves. Furthermore, the same parameter was computed by gradient boost [110].
- Peak Particle Velocity: this reflects the maximum velocity of the moving particles of an existing quarry blast. In this regard, many research efforts have been exerted relying on different ML models such as DT, SVM, ANN, etc. The performance of these models has reached valuable accuracy between 95 and 99.7% as studied in [36,111,112].
- Earthquakes and Quarry Blasts Discrimination: this denotes the classification between the wave generated by an earthquake and the one generated by a quarry blast. This critical application of ML in seismology has been properly investigated in the literature context, as in [1,113,114]. These models have developed several models such as XGB, CNN, ANN, etc., which achieved a discrimination accuracy range between 89 and 100%.
- Urban Planning Extension: ML can also play a significant role in estimating the increase in population and the consequent desired urban extension. In [115], the authors developed an ML model using multi-linear and nonlinear models for the extent of the population and PGA estimation.

8. Conclusions and Main Challenges

In this paper, various essential aspects of IoT-based EEWS relying on ML were provided to manage the earthquake disaster and to alleviate its consequences for preserving human lives. More particularly, we started with a brief discussion on the IoT system that plays a significant role in EEWS. Then, the survey portrayed a category of linear and non-linear ML models and addressed the metrics utilized for evaluating these models, targeting the ones involved in seismology. The paper also presented a taxonomy addressing the significant ML and IoT potentials for EEWS. Moreover, a generic integrated system using IoT was proposed in which ML can analyze different types of data formats observed by the EEWS entities. Finally, for a reliable EEWS, the ML models should be efficiently trained on an integration of different data types to be able to fit different areas of interest. Moreover, the used ML models for observations of earthquake parameters should be estimated by several evaluation metrics.

It is worth mentioning that EEWS based on IoT and ML would face various challenges, where we focus on the main challenges as follows. Some constraints should be accurately investigated such as data rate, energy efficiency, and high computational capabilities to fit the ML intelligence. Moreover, the use of ML for seismology is challenging as no unified model can be used for different geological areas. Last but not least, the high density of IoT devices needs an evolution of ML models to handle the system complexity.

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