Earthquake Prediction Using Expert Systems: A Systematic Mapping Study

Rabia Tehseen, Muhammad Shoaib Farooq * and Adnan Abid
Department of Computer Science, University of Management and Technology, Lahore 54770, Pakistan; f2017288003@umt.edu.pk (R.T.); adnan.abid@umt.edu.pk (A.A.)
* Correspondence: Shoaib.farooq@umt.edu.pk

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Abstract: Earthquake is one of the most hazardous natural calamity. Many algorithms have been proposed for earthquake prediction using expert systems (ES). We aim to identify and compare methods, models, frameworks, and tools used to forecast earthquakes using different parameters. We have conducted a systematic mapping study based upon 70 systematically selected high quality peer reviewed research articles involving ES for earthquake prediction, published between January 2010 and January 2020. To the best of our knowledge, there is no recent study that provides a comprehensive survey of this research area. The analysis shows that most of the proposed models have attempted long term predictions about time, intensity, and location of future earthquakes. The article discusses different variants of rule-based, fuzzy, and machine learning based expert systems for earthquake prediction. Moreover, the discussion covers regional and global seismic data sets used, tools employed, to predict earthquake for different geographical regions. Bibliometric and meta-information based analysis has been performed by classifying the articles according to research type, empirical type, approach, target area, and system specific parameters. Lastly, it also presents a taxonomy of earthquake prediction approaches, and research evolution during the last decade.

Keywords: Expert systems; Systematic Mapping Study (SMS), earthquake prediction; seismic data; Early-warning systems

1. Introduction

Earthquakes have been one of the most hazardous but least predictable natural disaster [1,2]. The occurrence of catastrophic earthquakes results in casualties, massive damage to the infrastructure, the vanishing of societies in a flash and a sudden downfall in the country’s economy [3,4]. There are many geographical factors that may cause an earthquake, including ground motion, heavy rainfall, rock bed material, regional tectonics and altitude [5]. There is a tremendous pressure on geologists and seismologists for the prediction of the time, place and strength of earthquakes [6]. Many researchers have claimed to predict earthquakes by observing multiple precursors such as recording the behavior of animals, observing an increase in temperature, emission of radon gas, and observing the change in seismicity patterns of the region, etc. References [7,8]. However, it is very hard to generalize and standardize these prediction algorithms as the precursors do not necessarily appear before every earthquake [9].

Earthquake prediction is a highly complicated task and many investigators have used different approaches for making forecasts. Among these different approaches the methods and algorithms that are based on a variety of expert systems (ES) have exhibited promising results in this area. The literature survey reveals that different approaches of expert systems including fuzzy, rule-based, neuro-fuzzy and machine/deep learning methods have been used to forecast future earthquake from historic and instrumental data. In practice, ES have also been efficiently used for risk analysis and assessment in
multiple areas such as, information technology (IT) [10], engineering [11], economics, healthcare [12], and civil engineering [13–15]. The motivation behind applying expert system technique for earthquake prediction lies in its noticeable effectiveness and reliability [16] of such approaches in other disciplines.

This research presents a systematic mapping study to facilitate the researchers and practitioners in understanding the fundamentals of earthquake prediction systems; evolution of research in this area, and prominent research directions in this area of research. To these ends, it presents an analysis of eighty four articles while presenting a classification scheme showing multiple aspects covered in the literature addressing earthquake prediction. The study presents a summary of various aspects of the expert systems given in multiple articles for earthquake prediction. It also determines the most frequently used variants of ES for the prediction of earthquake while highlighting the accuracy in prediction results claimed in multiple articles. It is pertinent to mention that to the best of our knowledge, no mapping study has been found about using ES for earthquake prediction. Furthermore, this mapping study not only covers the bibliometric aspects of the selected research articles, but also presents a taxonomy of approaches, variants of ES, their strengths and comparative analysis of their effectiveness in prediction accuracy, and the widely used seismic data sets. Lastly, the open research areas and future directions in this area have also been presented to the researchers working in this area.

There are certain limitations of this survey. These limitations relate to the selection of primary studies [17]. In order to ensure that as many relevant publications as possible have been included, we have identified search terms in several iterations. Terms related to ES and earthquake prediction were used in the search string. However, the list might not have been complete, and additional or alternative terms might have altered the final list of papers found [18]. The search was performed by using the Elsevier Scopus Digital Library. According to the statistics of the publications retrieved, we believe that most of the research on earthquake can be found in this electronic library. However, certain papers may have been overlooked due to the subscription limitations. Another threat is related to the handling of duplications, which might have slightly changed our results. Kappa measure has been used for making decisions about possible duplications. The data has been extracted from the primary studies and classified to generate the final results. The decision about which data to collect and how to classify the papers therefore depended on the judgement of the authors conducting the systematic mapping study [19]. The Kappa coefficient has resulted in 0.95 which indicated an agreement among the authors about data inclusion. Data extraction from prose could also result in a misclassification, but this problem was addressed by developing a classification scheme on the basis of widely accepted guidelines [17] and terminology proposed for use in [20]. It would, therefore, only have a minor influence on the classification scheme developed in this mapping study. Validity limitation refers to the missing studies, incorrect data extraction [21] and determining the incorrect relationship among multiple facets. To overcome this threat, we have clearly described the activities involved in publication selection and data extraction in multiple sections. The traceability between the data extracted and the conclusion drawn has been presented through bubble plots and frequency plots. The quality assessment problem is concerned with the quality of study selection [5,22,23]. The systematic mapping results were considered in regard to the seismic domain, and the validity of the conclusions drawn concerns the earthquake prediction context only. To focus on state of the art methods, we have applied time restriction in searching for published studies and have included the papers published during January 2010 till January 2020. The search string and the classification scheme presented in this paper may serve as a starting point for researchers working on the problem of earthquake prediction, and they can search for and categorize additional papers accordingly.

The rest of the article has been structured in the following manner. Section 2 presents the background of this study, while the research methodology of this study has been presented in Section 3. The analysis of all the selected and reviewed articles has been presented in Section 4. The analysis about the findings of the literature review has been discussed in Section 5. Lastly, the article has been concluded in Section 6.
2. Background

In this section, we have presented the general outline of the research work about using expert system for earthquake prediction. Multiple approaches, including rule-based, fuzzy, neuro-fuzzy and machine/deep learning methods have been used for earthquake prediction.

2.1. Fuzzy Expert System (FES)

The concepts of fuzzy set and fuzzy logic were introduced in 1965 by [20]. Fuzzy expert system accepts input as crisp variables and converts it into fuzzy variables. Fuzzy inference engine applies the rules suggested by an expert to formulate the knowledge base. Fuzzy variables combined with linguistic variables to generate membership functions. Techniques based on fuzzy logic have the benefits over multiple procedures due to their ability to combine with linguistic variables. These fuzzy variables would be converted back into the crisp variable to generate output through the process called defuzzification. Fuzzy logic is more suitable in the situations where a greater number of uncertainties have been involved, such as, earthquake prediction and in the scenarios where an approximate but quick solution is required. Fuzzy logic is not a logic that is fuzzy itself, but a logic that can be used to demonstrate fuzziness [21]. The vagueness of fuzzy logic has been highlighted in [10] by examining the events that cannot be recorded statistically such as crack in the underground fault, etc. A new attenuation relationship has been proposed in [8] using three fuzzy input sets including epicentral distance, earthquake magnitude and intensity using earthquake data set of Taiwan and United states of America (USA). A normalized fuzzy ground motion model has been demonstrated using a rational design tool through a combination of natural language with seismic data statistics to quantify response frequency. The earthquake pattern in the Zagros range has been examined in [9] using fuzzy rule-based ES model for some earthquakes. The proposed model has been evaluated using the Molchan statistical procedure by comparing complicated reasoning procedure of the forecasting model with knowledge simulation provided by human experts using the datasets of Iran. A rock burst forecasting model has been presented in [13] by studying the seismic features of coal mining in China. In this study, Gaussian shaped membership function has been combined with the exponential distribution function using reliability theory. The comprehensive forecasting result was obtained by integrating the maximum membership degree principle (MMDP) and the variable fuzzy pattern recognition (VFPR) method. The performance of the proposed model has been evaluated using seismic data collected over the period of four months. The proposed model has been able to forecast the rock burst incident in the coal mine of China. Multiple algorithms have been combined for development of the hybrid prediction model [24, 25]. Ionospheric disturbance has been examined in [26] and a fuzzy logic-based gradient descent method has been proposed to forecast the ionospheric change parameters. The gradient descent estimated values were used to tune the membership function. The satisfactory performance has been observed during evaluated of the proposed model using data collected from two geomagnetic storms on the low latitude. Reference [1] has claimed earthquake prediction on the bases of the classification of seismic signals.

2.2. Rule Based Expert System (RBES)

In RBES domain knowledge is represented by a set of rules and the current situation is presented with the set of facts stored in the database. An inference engine is responsible to match the rule with the fact. The fired rule may change the set of facts and add new facts. Many researchers have used rule based expert system for earthquake prediction. A belief rule based expert system has been presented in [27] to predict the earthquake under uncertainty. Specific animal behavior in response to environmental and chemical changes has been examined for earthquake prediction. Reference [20] developed rules from historical earthquake data using predicate logic. These rules have been mathematically validated on real time data. Prediction is performed through RBES that takes current earthquake attributes for prediction of future earthquake.
2.3. Neuro Fuzzy Expert System (NFES)

Fuzzy logic is combined with neural networks to develop expert systems. Fuzzy logic provided a high level reasoning procedure by including domain information from the domain expert and neural network has been used to develop low level computational structures. The Neuro fuzzy expert system has been used in many articles to analyze multiple aspects of data for earthquake predictions. Reference [28] combined grid partition, subtractive clustering and fuzzy C-means (FCM) for the development of models using NFES structure. Reference [5] applied NFES to compute land sliding susceptibility using statistical index (WI). Reference [22] collected geographical information to pass through six different membership functions for measuring land sliding susceptibility using NFES. Many researchers have analysed combination of artificial neural network and fuzzy inference system [29–32]. Earthquake attribute such as magnitude, depth, longitude and latitude has been studied in [33] to provide input to NFES for computation of the future earthquake.

2.4. Machine Learning (ML)

Machine Learning has been widely used for making earthquake predictions due to their ability to improve over time. With the huge amount of earthquake instrumental data, machine learning approaches are capable enough to improve efficiency and accuracy in earthquake prediction. Multiple machine learning methods including, Artificial Neural Network (ANN), Support Vector machine (SVM), K-nearest neighbour (KNN), Native Bayes (NB) and random forest algorithms have been exercised for earthquake prediction. Reference [34] applied Artificial Neural Networks, Support Vector Machines and Random Forests to perform temporal investigations on earthquake catalogue of Cyprus region and calculated sixty seismic indictors for making short term earthquake prediction. Reference [35] applied different machine learning algorithms namely support vector machine (SVM), K-nearest neighbor (KNN), random forest (RF), and Naïve Bayes (NB) algorithms in R programming language for earthquake prediction using seismic dataset of India. Reference [36] studied the thermal anomalies that happened before the earthquake occurred in Imphal, India, in 2016 and investigated multiple seismic facts through satellite data using machine learning algorithms for an earthquake. Reference [37] collected records of aftershocks of the Kermanshah (Iran) Earthquake and applied different machine learning (ML) algorithms, including Naïve Bayes, k-nearest neighbors, a support vector machine, and random forests to predict future earthquakes by observing aftershock patterns. Reference [38] exercised neural networks for earthquake signal detection. Reference [39] listed the detailed description of the monitoring techniques used for earthquake prediction. References [40,41] presented a comprehensive review of machine learning methods used for earthquake prediction. Reference [42] made seismic hazards forecasts by using two different machine learning based methods for both spatial and space-time prediction of strong earthquakes. Reference [43] determined the significance of shallow land slide triggers in making earthquake forecasts using machine learning methods. Reference [44] improved the conventional waveform correlation method and presented a new method for detection of seismic signals for monitoring the false alarms using machine learning. Reference [45] identified, classified and reviewed the prominent machine/deep learning models used in energy systems. Reference [46] discussed multiple artificial intelligent models utilized for hydrologic model prediction in past decade. Reference [47] highlighted the opportunities and challenges presented by big data for informed decision-making. Reference [48] developed a food forecast model using multiple optimization methods.

3. Research Methodology

The objective of systematic mapping study is to present an overview of the research area and quantify the results presented by the selected studies. We intend to determine the research trends by mapping the frequency of publications over time. For this purpose, we have adopted the methodologies
of [45,46] and performed a number of activities as shown in the Figure 1. Our main goal is to provide deep inside of expert system based solutions proposed for earthquake prediction in literature.

3.1. Defining Research Questions

We have addressed three research questions in this mapping study. These research questions have served as a guide for the classification of research articles. A set of research questions has been described in Table 1.

Table 1. Set of research questions (RQs) and their motivation.

| Research Question (RQ) | RQ Statement | Motivation |
|------------------------|--------------|------------|
| RQ 1                   | What are the bibliometric key facts of expert systems (ES) based earthquake prediction publications? | The intentions of this research question is to find out the number of publications that have been published. |
| RQ 1.1                 | How many studies have been contributed from January 2010 to January 2020? | The main intention is to categorize the selected publications through the schema established by [17,49]. Therefore, we use the research type facets given by Zhang et al. [49]. Based on these type facets, we wanted to find out multiple research contexts, including the type of the research, empirical type of the research, approaches used in the research and areas targeted by the researchers for data extraction. |
| RQ 1.2                 | What are the venues where these studies have been published? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 2                   | Which research type facets do the identified publications address? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 2.1                 | What is the type of research conducted in the publication? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 2.2                 | What is the empirical type of the research conducted in the publication? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 2.3                 | What approach has been used by the researcher? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 2.4                 | Which area has been targeted by the research for data collection? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 3                   | What is the type and other key aspects of proposed Expert System (ES) in the classified publications? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 3.1                 | What type of expert system has been proposed in the selected studies? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 3.2                 | Which input domain does the proposed ES address? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 3.3                 | How many input attributes are passed to the proposed ES? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 3.4                 | What is the type of the input attributes passed to the proposed ES? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 3.5                 | Which type of prediction logic has been used by the proposed ES? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |
| RQ 3.6                 | Which tool or technique has been used to develop the proposed ES? | The main aim is to determine the types of proposed ES used for earthquake prediction in the articles published during January 2010 till January 2020. This question is helpful in highlighting the other parameters of the proposed ES like input domain, number of input attributes passed, type of the input attributes, prediction logic, the tools and techniques used in the articles have been categorized. |

3.2. Search and Selection Strategy

After defining research questions, next activity was to select the sources from where the articles would be retrieved. For this purpose, we have adopted the searching strategy given in [47,48] and...
have developed a comprehensive search string based on the key terms given in Table 2. Articles have been collected from Elsevier Scopus digital library (www.scopus.com). The terms stated in Table 2 have been used to develop the search string for searching articles from the given sources.

Table 2. Distinct key terms used in developing the search strings.

| AND Terms | OR Terms |
|-----------|----------|
| Earthquake | Rule based, Fuzzy, Frame based |
| Indicator | Machine Learning, Deep learning, Expert system |
| Prediction | Seismic, Tremor |
| | Precursor, Feature |
| | Predict* (* means wildcard) |

3.2.1. Identification of Search String

The primary keywords were selected as key identifiers of work in the field of earthquake prediction using expert system. A set of distinct keywords is listed in Table 2.

This mapping study has been conducted to examine the literature about earthquake prediction using expert systems. We have used multiple key terms like fuzzy, frame based and rule based methods for extracting such articles that describe the use of expert systems for earthquake prediction, but does not necessarily have an expert system explicitly written in their titles. In the same way, earthquake has been presented as a seismic event or a tremor in some studies, so we have also included these keywords. The change in the behaviour of precursors has been studied in many articles for earthquake prediction. Therefore, we have also included a few keywords describing the indicators of future earthquakes. Search string has been developed after defining key terms. The following search string has been used to search articles from Elsevier Scopus digital library. We have included the articles published from January 2010 till January 2020.

3.2.2. Screening and Selection Criteria

Screening of the articles has been performed after retrieval. The main purpose is to select most relevant articles. Every paper was retrieved and evaluated by considering title, abstract, keywords, introduction and conclusion. The inclusion and exclusion criteria given in Table 3 have been used for article selection. We have included only those articles that satisfy the inclusion criteria given in Table 3. We have excluded those papers which have been retrieved from multiple sources or representing different stages of the same project. For inclusion of the articles that have identical abstracts we have calculated Kappa coefficient. The papers that are not written in the English language have also not been included. The thesis has also been excluded because they normally cover multiple aspects of the problem. Papers with unclear methodology and not satisfying our quality criteria have also been excluded.

Table 3. Inclusion and Exclusion Criteria.

| Inclusion Criteria (IC) | Description |
|-------------------------|-------------|
| IC1 | Articles in which an expert system has been developed for earthquake prediction |
| IC2 | Articles in which earthquake precursors have been analyzed |
| IC3 | Articles presenting unique and new ideas |
| IC4 | Literature published as book chapter and technical reports for earthquake prediction |
| IC5 | Articles with identical abstracts (on the basis of Kappa coefficient) |

| Exclusion Criteria (EC) | Description |
|-------------------------|-------------|
| EC1 | Duplicates and identical titles |
| EC2 | Papers not in English language |
| EC3 | Thesis (cover several different aspects) |
| EC4 | Papers with unclear methodology |
| EC5 | Papers not satisfying quality criteria |
We have taken a good care of article quality selection in the article selection process. To ensure high quality in article selection, criteria given in [19] have been adopted and elaborated in Table 4.

Table 4. Quality Criteria.

| Sr. | Criteria                        | Type       | Weight |
|-----|---------------------------------|------------|--------|
| a.  | Study Presents contribution     | Yes        | 1      |
|     |                                 | No         | 0      |
|     |                                 | Partially  | 0.5    |
| b.  | Study presents solution         | Yes        | 1      |
|     |                                 | No         | 0      |
|     |                                 | Partially  | 0.5    |
| c.  | The study presents empirically  | Yes        | 1      |
|     | validated results               | No         | 0      |
|     |                                 | Partially  | 0.5    |

Search Process resulted in the retrieval of 2137 articles that passed through multiple phases. In the first phase, our search string has retrieved 2137 research articles. After passing through multiple screening phases of selection criteria seventy articles have been considered original, non-duplicate, with clear methodology and satisfying our quality criteria. The coefficient has been calculated to determine the relevance among the articles. In every screening phase, two authors of this mapping study have been asked to make judgment about the relevance of the article by selecting any choice from “accept”, “reject” or “differ” options. In case of difference in the opinion of both judges, comprehensive discussion has been carried out to a decision point has been reached in the form of acceptance or rejection.

3.3. Data Extraction and Synthesis

It is based on providing a set of answers to the research questions. Table 5 represents the data that we intend to extract by asking research questions prescribed in Table 1.

Table 5. Data extracted through each research question.

| Research Questions (RQs) | Data Extracted                                                                                          |
|-------------------------|----------------------------------------------------------------------------------------------------------|
| RQ 1                    | Number of publications contributed in the given time period has been determined.                         |
| RQ 1.1                  | A main venue where the study has been published has been noted.                                         |
| RQ 2                    | Research type (solution, evaluation, experience) has been determined.                                     |
| RQ 2.1                  | Empirical type (Experiment, survey, case study) has been determined.                                      |
| RQ 2.2                  | The approach used (model, method, guideline, framework, tool) has been noted.                            |
| RQ 2.3                  | Seismic zone (global, regional) focused by the study has been determined.                                |
| RQ 3                    | Type of the proposed expert system (Fuzzy expert system, rule based expert system, Neuro fuzzy expert system) has been noted.
| RQ 3.1                  | Identification of the input domain i.e., quake or precursive                                            |
| RQ 3.2                  | Number of input attributes, i.e., single or multiple that have been passed to the proposed ES for earthquake prediction. |
| RQ 3.3                  | Type of the input attributes (numeric or discrete) has been determined.                                  |
| RQ 3.4                  | Prediction logic (inductive or deductive) used by the proposed expert system has been noted.            |
| RQ 3.5                  | Tools and techniques used to develop the proposed expert system given in the studies have been categorized. |
techniques used in the articles have passed through an evaluation process before its implementation. Experience papers presented the personal experiences of the author explaining how something has been done in practice. Empirical type illustrated that an experiment, survey, or case study has been performed in the selected article. We have also collected the information regarding focused seismic zone through RQ2. Detailed type facets of the proposed ES for prediction of earthquake have been listed in the classification Table 6. We have provided a set of distinct keywords in Figure 2 to explain the contents of Table 6. The relationship between number of publications and the type facets determined through RQ2 has been shown in Figure 3.

Figure 2. Set of distinct keywords used to populate classification Table 6.

Figure 3. Relationship between number of publications (n) and the type facets.
### Table 6. Classification Table.

| Ref. | Bibliometric Facts | Type Facets | System Specific Information | Quality Ranking |
|------|--------------------|-------------|----------------------------|-----------------|
|      | Publication Channel | Publication Year | Research Type | Empirical Type | Approach | Target Area | Proposed ES type | Input Domain | Input Attribute | Input Attribute type | Data Type | Prediction Logic | Tools and Techniques | (a) | (b) | (c) | Score |
| [1]  | Journal 2014       | Eva CS Mod RL | FES PR ML UV | Dis IN SW | 1 0.5 0.5 2.0 |
| [2]  | Journal 2017       | Eva Ext Met RL | FES QE SL DV | Num IN AM | 1 0.5 1 2.5 |
| [3]  | Journal 2017       | Eva Ext Mod RL | Other QE ML | DV Num DD SW | 1 0.5 1 2.5 |
| [4]  | Journal 2018       | Eva Ext Met RL | NFES PR SL UV | Dis IN AM | 1 0.5 0.5 2.0 |
| [5]  | Journal 2015       | Eva Ext Met RL | FES QE ML DV | Num IN SW | 1 0.5 1 2.5 |
| [6]  | Journal 2015       | Eva Ext Mod RL | FES QE ML PE Num IN AM | 1 0.5 1 2.5 |
| [7]  | Confe 2012         | Sol Ext Met RL | FES PR ML DV | Dis IN Other 0.5 1 1 2.5 |
| [8]  | Journal 2014       | Eva Ext Mod RL | FES PR ML DV | Dis IN SW | 1 0.5 1 2.5 |
| [9]  | Journal 2017       | Eva CS Met RL | Other QE ML | DV Num IN SW | 1 0.5 1 2.5 |
| [10] | Journal 2017       | Eva CS Met RL | Other QE ML | DV Num IN SW | 1 0.5 1 2.5 |
| [11] | Journal 2017       | Eva CS Met RL | Other QE ML | DV Num IN SW | 1 0.5 1 2.5 |
| [12] | Journal 2018       | Sol Ext Mod RL | FES QE SL DV | Num IN SW | 0.5 1 1 2.5 |
| [13] | Book 2017          | Eva CS Met RL | FES QE SL DV | Dis IN SW | 0.5 1 0.5 2.0 |
| [14] | Journal 2017       | Exp Sur Met RL | FES QE ML PE Dis | IN Other 0.5 0.5 0 | 1.0 |
| [15] | Journal 2013       | Exp Sur Mod GL | RBES PR SL PE | Dis DD SW | 0.5 0.5 0 | 1.0 |
| [16] | Journal 2013       | Eva Ext Mod RL | RBES PR ML PE | Dis IN Other 0.5 1 1 2.5 |
| [17] | Journal 2016       | Eva Sur Met RL | FES QE ML PE | Dis Num DD AM | 1 0.5 0 | 1.5 |
| [18] | Confe 2015          | Eva Ext Mod GL | RBES QE ML | DV Dis IN SW | 1 0.5 1 2.5 |
| [19] | Journal 2014       | Eva Ext Mod GL | RBES QE ML | DV Dis IN SW | 1 0.5 1 2.5 |
| [20] | Journal 2018       | Eva Ext Met GL | FES QE ML | DV Dis DD AM | 1 0.5 1 2.5 |
| [21] | Journal 2018       | Eva Ext Met GL | NFES QE ML | DV Dis IN SW | 1 0.5 1 2.5 |
| [22] | Journal 2015       | Exp CS Met RL | FES QE SL PE | Dis IN Other 0.5 0.5 0.5 1.5 |
| [23] | Confe 2016          | Exp CS Met RL | FES QE ML DV | Dis IN Other 0.5 0.5 0.5 1.5 |
| [24] | Confe 2010          | Eva Ext Met RL | Other QE ML PE | Num DD AM | 1 0.5 1 2.5 |
| [25] | Journal 2017       | Sol CS Mod RL | Other PR SL PE | Dis IN SW | 0.5 1 0.5 2.0 |
| [26] | Journal 2018       | Eva Ext Mod GL | RBES PR SL PE | Dis IN AM | 1 0.5 1 2.5 |
| [27] | Journal 2012       | Sol Sur Mod GL | FES PR ML PE | Num IN AM | 0.5 1 0 | 1.5 |
| [28] | Journal 2015       | Exp Sur Gle GL | NFES PR SL PE | Num IN SW | 0.5 0.5 0 | 1.0 |
| [29] | Journal 2015       | Eva Ext Mod RL | NFES QE ML PE | Num IN AM | 1 0.5 1 2.5 |
| [30] | Journal 2018       | Eva CS Mod RL | NFES PR SL DV | Dis IN SW | 1 0.5 0.5 2.0 |
| [31] | Journal 2014       | Exp Sur Gle GL | NFES QE ML DV | Num DD SW | 0.5 0.5 0 | 1.0 |
| Ref. | Publication Channel | Publication Year | Research Type | Proposed ES type | Input Domain | Input Attribute | Input Attribute type | Data Type | Prediction Logic | Tools and Techniques | Score |
|------|---------------------|------------------|---------------|-----------------|--------------|----------------|---------------------|-----------|-----------------|----------------------|-------|
| [34] | Journal 2020       | Evac             | FW            | RL Ml           | QE ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [35] | Confe 2020          | Eva              | Ext           | RL Ml           | QE ML       | FE             | Dis DD              | SW        | 0.5             | 0                    | 1     |
| [36] | Journal 2020       | Exp              | CS Met        | RL Ml           | QR SL       | DV             | Dis DD              | SW        | 0.5             | 1                    | 2     |
| [37] | Journal 2019       | Exp              | Ext Met       | RL Ml           | QR SL       | FE             | Dis DD              | SW        | 0.5             | 1                    | 2     |
| [38] | Confe 2019          | Exp              | Ext Met       | GL Ml           | QR ML       | FE             | Dis DD              | AM        | 0.5             | 1                    | 2.5   |
| [39] | Confe 2019          | Exp              | Sur Gle       | GL Ml           | PR ML       | DV             | Dis IN              | AM        | 0.5             | 0                    | 1     |
| [40] | Confe 2019          | Exp              | Sur Gle       | GL Ml           | PR ML       | DV             | Dis IN              | AM        | 0.5             | 0                    | 1     |
| [41] | Journal 2019       | Eva              | Ext Met       | RL Ml           | QR ML       | FE             | Dis DD              | AM        | 0.5             | 1                    | 2.5   |
| [42] | Confe 2019          | Eva              | Ext Met       | RL Ml           | QR ML       | FE             | Dis DD              | AM        | 0.5             | 1                    | 2.5   |
| [43] | Journal 2018       | Exp              | CS Met        | GL Ml           | QR ML       | DV             | Num IN              | AM        | 0.5             | 1                    | 2.5   |
| [44] | Journal 2019       | Exp              | CS Met        | GL Ml           | QR ML       | DV             | Num IN              | AM        | 0.5             | 1                    | 2.5   |
| [45] | Journal 2019       | Exp              | CS Met        | GL Ml           | QR ML       | DV             | Num IN              | AM        | 0.5             | 1                    | 2.5   |
| [46] | Journal 2018       | Exp              | CS Met        | GL Ml           | QR ML       | DV             | Num IN              | AM        | 0.5             | 1                    | 2.5   |
| [47] | Journal 2018       | Exp              | CS Met        | GL Ml           | QR ML       | DV             | Num IN              | AM        | 0.5             | 1                    | 2.5   |
| [48] | Journal 2017       | Eva              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [49] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [50] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [51] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [52] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [53] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [54] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [55] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [56] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [57] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [58] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [59] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [60] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [61] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [62] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [63] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [64] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [65] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [66] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
| [67] | Journal 2017       | Exp              | Ext Met       | RL Ml           | QR ML       | FE             | Num DD              | AM        | 0.5             | 1                    | 2.5   |
Table 6. Cont.

| Ref. | Publication Channel | Publication Year | Research Type | Empirical Type | Approach | Target Area | Proposed ES type | Input Domain | Input Attribute | Input Attribute type | Data Type | Prediction Logic | Tools and Techniques | (a) | (b) | (c) | Score |
|------|---------------------|------------------|---------------|----------------|----------|-------------|------------------|--------------|-----------------|---------------------|-----------|----------------|---------------------|-----|-----|-----|-------|
| [60] | Conference          | 2017             | Eva           | CS             | Mod      | RL          | ML               | QE           | ML              | PE                  | Num       | IN             | SW                  | 1   | 0.5 | 0.5 | 2    |
| [61] | Conference          | 2015             | Eva           | CS             | Met      | RL          | ML               | QE           | ML              | PE                  | Num       | IN             | SW                  | 1   | 0.5 | 0.5 | 2    |
| [70] | Journal             | 2015             | Eva           | Ext            | Mod      | GL          | ML               | QE           | ML              | PE                  | Num       | IN             | SW                  | 1   | 0.5 | 1   | 2.5  |
| [71] | Journal             | 2015             | Eva           | CS             | Mod      | RL          | ML               | PR           | ML              | LV                  | Dis       | DD             | SW                  | 1   | 0.5 | 0.5 | 2    |
| [72] | Journal             | 2013             | Eva           | CS             | Met      | RL          | ML               | QE           | ML              | LV                  | Dis       | DD             | SW                  | 1   | 0.5 | 0.5 | 2    |
| [73] | Journal             | 2013             | Eva           | CS             | Met      | RL          | ML               | PR           | SL              | LV                  | Dis       | DD             | SW                  | 0.5 | 0.5 | 0.5 | 1.5  |
| [74] | Journal             | 2016             | Sol           | Ext            | Met      | GL          | ML               | QE           | ML              | LV                  | Num       | IN             | SW                  | 0.5 | 1   | 1   | 2.5  |

Notes: Publication Channel: Confe = Conference; Research Type: Eva: Evaluation, Exp: experience, Sol: Solution; Empirical Type: CS: Case study, Ext: Experiment, Sur: Survey; Approach: Mod: Model, Met: Method, Gle: Guideline, FW: Framework; Target Area: RL: Regional, GL: Global; Proposed ES type: Ml: Machine learning, FES: Fuzzy expert system, NFES: Neuro fuzzy expert system, RBES: Rulebased expert system; Input Attribute: ML: Multiple, SL: Single; Input Attribute Type: PE: Primitive, DV: Derived; Data Type: Num: Numeric, Dis: Discrete; Input domain: QE: Quake, PR: Precursive; Prediction Logic: IN: Inductive, DD: Deductive; Tools and Techniques: SW:Software, Alg:Algorithm.
We have collected information about the type of ES such as FES, RBES and NFES proposed for earthquake prediction in the selected articles through RQ3. The key aspects of the proposed ES including input domain, number of input attributes, type of input attributes, data type, prediction logic, tools and techniques used for prediction of earthquake have been discussed in Figure 4. Input domain describes the input variables taken by the system to predict an earthquake. It can be either ‘Quake variables’ like latitude, longitude, magnitude, primary wave (P-Wave) attributes, etc. or ‘Precursors variables’ like ionosphere readings, earth’s thermal variations via satellites etc. Input attributes can be single or multiple. Some systems predict using single quake or precursor variable. Many articles used multiple input variables for earthquake prediction. Input attributes type can be primitive or derived. Some techniques directly consume an input parameter and others manipulate (derive) before use. The proposed ES uses variables in primitive form or transforms it into some other form before consuming it. The data type can be numerical or discrete. Prediction logic can be inductive or deductive. Inductive logic has no absolute proof from premises to conclusions, e.g., fuzzy sets. Deductive prediction logic determined an absolute proof from premises to conclusions.

![Figure 4. Relationship between number of studies and system specific parameters of ES.](image)

### Classification of Articles

We have classified the articles to determine multiple parameters summarized in Table 6 presenting the bibliographic values, research type facets, type of the expert system used and other key aspects of the ES proposed in these articles for earthquake prediction. Quality criteria defined in Table 4 have also been applied to categorize the articles accordingly. Classification Table 6 had been developed on the basis of research questions given in Table 1 and the quality criteria prescribed in Table 4.

### 4. Analysis

The results obtained from the research questions (as given in Table 1) have been presented in Table 6. All articles have been selected to illustrate their relevance and contribution in the earthquake prediction process by providing an answer to every research question.

#### 4.1. Basic Analysis

After deep investigation eighty four articles have been selected and main approaches for earthquake prediction including machine learning, neuro-fuzzy, fuzzy and rule-based approaches have been reviewed.
These articles were thoroughly analyzed to answer the research questions (RQs) given in Table 1. We have summarized the results obtained from RQs in Table 6. A set of distinct keywords to explain the contents of Table 6 has been given in Figure 2.

Table 6 describes the list of the selected articles and classifies them by extracting bibliometric facts, type facets, system specific information and quality ranking. Quality scores obtained by every article have been summed up to find the total score. According to Table 6, the average scores obtained by the articles are 1.5. The publications having scored greater than 1.5 are above average and the publications having scores below 1.5 are considered below average. Detailed description of classified results after application of quality criteria has been given in Table 6.

Table 7 illustrates the trend of researcher regarding article submission in multiple sources. It lists down multiple sources, publication channels, and the frequency of articles in each source.

| Source                                                                 | Channel                     | Reference |
|-----------------------------------------------------------------------|-----------------------------|-----------|
| International Conference on Natural Computation (ICNC)                | Conference                  | [75]      |
| Pure and Applied Geophysics                                           | JournaL                     | [76]      |
| Expert Systems with Applications                                      | Journal                     | [1,9]     |
| IEEEACCESS                                                             | Journal                     | [49]      |
| International Journal of Computer Applications                        | Journal                     | [77]      |
| Proceedings of Indian National Science Academy                        | Journal                     | [78]      |
| Earth Science Informatics                                              | Journal                     | [65,79]   |
| Journal of Indian Society of Remote Sensing                           | Journal                     | [80]      |
| Bulletin of Engineering Geology and Environment                       | Journal                     | [23,60,81,82] |
| Natural Hazards                                                       | Journal                     | [2,4,12,22,28,31,83] |
| Knowledge Based Systems                                               | JournaL                     | [17,19]   |
| Journal of Environmental Radioactivity                                | Journal                     | [54]      |
| International Journal of Coal Geology                                | Journal                     | [53]      |
| Computer-Aided Civil and Infrastructure Engineering                   | Journal                     | [15]      |
| Applied Sciences                                                      | Journal                     | [10]      |
| International Journal of Disaster Risk Reduction                      | Journal                     | [11]      |
| Tunnelling and Underground Space Technology                           | Journal                     | [13]      |
| PLoS ONE                                                              | Journal                     | [19,56]   |
| Environmental Earth Sciences                                         | Journal                     | [5,52,84-86] |
| International Journal of Fuzzy Systems                               | Journal                     | [32]      |
| Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications | Journal                     | [27]      |
| Applied Soft Computing                                                | Journal                     | [87]      |
| Journal of Intelligent Information Systems                            | Journal                     | [20]      |
| Geodesy and Geodynamics                                              | Journal                     | [26]      |
| Environmental Monitoring Assessment                                   | Journal                     | [21]      |
| Earth Science Informatics                                             | Journal                     | [65,79]   |
| International Journal of Computer Information Systems and Industrial Management Applications | Journal                     | [30]      |
| Biostatistics and Biometrics                                          | Journal                     | [6]       |
| International Journal of Engineering Research & Technology            | Journal                     | [21]      |
| Journal Geological Society of India                                   | Journal                     | [50]      |
| Journal of Sustainability Science and Management                      | Journal                     | [16]      |
| Journal of Chemical and Pharmaceutical Sciences                       | Journal                     | [30]      |
| Acta Geophysica                                                       | Journal                     | [3]       |
| International Conference on Fuzzy Systems and Knowledge Discovery (FSKD) | Conference                  | [25,35,88] |
| International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems | Journal                     | [7,21]    |
| International Conference on Information Management, Innovation Management and Industrial Engineering | Conference                  | [51]      |
| Analysis & Computation Specialty Conference                          | Conference                  | [8]       |
| Soil Dynamics and earthquake engineering                              | Journal                     | [34,64,69] |
| Lecture notes on electrical engineering                               | Conference                  | [35]      |
| Advances in intelligent system and computing                          | Journal                     | [36]      |
| ISPR- International Journal of geo information                        | Journal                     | [37]      |
| Seismological Research Letter                                         | Conference                  | [38,40]   |
| Geophysical Research Letter                                           | Conference                  | [39,63]   |
| CEUR workshop proceedings                                             | Conference                  | [41]      |
| Geosciences                                                           | Journal                     | [42,59]   |
| Proceedings of SPIE-the international society of optical engineering  | Conference                  | [43]      |
| Bulletin of seismosesological society of America                      | Journal                     | [44]      |
| Neural processing letter                                              | Conference                  | [56]      |
| Proceedings-IEEE 4th International conference on big data, computing services and applications | Conference                  | [97]      |
| Lecture notes on computer science                                     | Conference                  | [61]      |
| Geomagnetics, Natural hazards and risks                               | Journal                     | [62]      |
| International Journal of SWARM intelligence research                  | Journal                     | [66]      |
| Neural computing and application                                      | Journal                     | [67]      |
| Proceedings- 14th international conference on frontiers of information technology | Conference                  | [68]      |
| Proceedings- 9th international conference on application of information and communication technology | Conference                  | [70]      |
| Bollettino deGeoFisica Teorica ed applicata                           | Journal                     | [71]      |
| Applied soft computing journal                                       | Journal                     | [71]      |
| Journal of King Saud University                                       | Journal                     | [74]      |
Two dimensional studies (as described in Table 8) have been conducted to highlight seismically active zones of the world. In the first dimension, researchers have evaluated the data of specific regions, whereas in the second dimension, researchers have analyzed overall earthquake data of the world in their articles. Table 8 presented the zones (regional or global) with their geographical dimension and their location on the tectonic plates. Table 8 will facilitate the researchers in determining that which tectonic zone is being mostly explored and analyzed by the practitioners.

Table 8. Target area representing the Geographic dimensions.

| Target Area       | Geographic dimension                                           | Ref.                              |
|-------------------|-----------------------------------------------------------------|-----------------------------------|
| Worldwide         | Global                                                          | [7,16,19–21,27,30,33,38–41,43,44,56,57,60,63,70,74,77,79] |
| Japan             | North American plate+Pacific plate+Pphilipine sea plate         | [61,85]                           |
| California        | North American plate+Pacific plate                              | [10,31,42,59,64,87]              |
| China             | Eurasian plate+Indian plate+Philipine sea plate                 | [2,12,13,23,25,49,51,55,75,88]   |
| Taiwan            | Eurasian plate + Philippine sea plate                           | [8]                              |
| Pakistan          | Eurasian plate + Indian plate                                   | [3,51,53,54,68,89]               |
| Italy, Turkey     | Eurasian plate+ African plate                                   | [15,32,70,76]                    |
| Greece, Azerbaijan| Eurasian plate+Arabian plate                                    | [86]                             |
| Morocco           | African plate                                                   | [1]                              |
| Nepal, Israel     | Indian plate+ African plate                                     | [18,50]                          |
| India             | Indian plate                                                    | [24,26,35,36,78]                 |
| Iran              | Iranian plate                                                   | [5,6,9,22,28,37,71,82,83]        |
| Saudi Arabia      | Arabian plate                                                   | [52]                             |
| Ethiopia          | Arabian plate+Somali plate+Nubian plate                         | [86]                             |
| Caraga            | Philippine sea plate                                            | [14]                             |
| Vietnam, Malaysia | Somali plate                                                    | [80,84]                          |
| Chile             | Nazca plate                                                     | [10,17,58,71,72]                 |
| Republic of Croatia| Apulian Plate                                                  | [65]                             |
| Cyprus            | African plate+Eurasian Plate +Arabian plate                     | [34]                             |

The researchers of the selected articles have evaluated their work using various tools and techniques including software, algorithms and other such as index normalization etc. These tools and techniques have been summarized in Table 9.

Table 9. Tools and Techniques applied in the literature for ES development.

| Tools and Techniques                              | %   | Reference                                      |
|---------------------------------------------------|-----|-----------------------------------------------|
| MATrix Laboratory (MATLAB)                        | 41  | [1,3,6,7,9–14,16,19,22,26,30,32,33,76,79,81,84,87] |
| Database Index normalization                      | 4   | [23,55]                                       |
| Generalized Langevin equation (GLE)               | 1.8 | [51]                                          |
| Subsidence Coefficient calculator                 | 1.8 | [75]                                          |
| Predicate (PRED) in C++                           | 1.8 | [88]                                          |
| Annealing, Sparsespike                            | 1.8 | [25]                                          |
| Classification and regression tree(CART)           | 1.8 | [49]                                          |
| Fuzzy C-mean                                      | 4   | [28,77]                                       |
| Upgraded IF THEN ELSE                            | 4   | [27,83]                                       |
| Normalized fuzzy peak ground acceleration (FPGA)   | 1.8 | [8]                                           |
Table 9. Cont.

| Tools and Techniques                                                      | %   | Reference |
|---------------------------------------------------------------------------|-----|-----------|
| Predicate Logic                                                           | 7   | [17,24,30,86] |
| Mean absolute error (MAE), Root mean square error (RMSE)                  | 1.8 | [54]     |
| Earth resources data analysis system (ERDAS) model maker                  | 1.8 | [51]     |
| 3Dimensional seismic tomography                                           | 1.8 | [79]     |
| Mean square error (MSE)                                                   | 4   | [31,53]  |
| Rapid miner software, frequency, pattern growth algorithm                 | 1.8 | [20]     |
| Adobe                                                                     | 1.8 | [89]     |
| Geological carbon storage (GCS) analyzer- Moncarle                         | 1.8 | [85]     |
| Fuzzy probablistic seismic hazard analyzer (FPSHA)                        | 1.8 | [2]      |
| FURIA                                                                     | 1.8 | [80]     |
| ArIGIS                                                                    | 1.8 | [81]     |
| Saga                                                                       | 1.8 | [83]     |
| Aeronautical reconnaissance coverage Geographic information system (ARC/INFO GIS) | 1.8 | [84] |
| Geographic information system (GIS), Multi criteria decision analysis (MCDA) | 4   | [15,82] |
| Multilayer Preceptron - Rule Based (MLP-RB)                               | 1.8 | [21]     |
| Nearest neighbor Invariant Riemannian metric (AIRM)                       | 1.8 | [32]     |
| WI (Weighted index)                                                       | 1.8 | [5]      |
| Knowledge extraction based on evolutionary learning (KEEL)                | 1.8 | [10]     |
| Particle SWARM Optimization (PSO)                                         | 1.8 | [56]     |
| Apache SPARK                                                              | 1.8 | [59]     |
| Kernal Fisher Discriminant Algoritthm (KFDA)                              | 1.8 | [60]     |
| Novel earthquake early warning system (NEEWS)                             | 1.8 | [64]     |

Accuracy of results obtained through the proposed expert system for making earthquake predictions using a training set (TS) or independent test set (ITS) has been listed in Table 10.

4.2. Key Facts of Expert System Based Earthquake Prediction Publications

Different publication channels, and frequency of publications per source have been presented in Table 7. Number of articles published per year from January 2010 to January 2020 along with the primary source where the article has been submitted is determined. Different publication channels have been identified, including conferences, journals, technical report and book chapters. Around 75% of the selected papers have been published in peer reviewed journals, 24% have presented at conferences, workshops, and symposia. 4% technical reports and book chapters have also included in this systematic mapping study.

4.3. Research Type Facets Addressed by the Identified Publications

For deep investigation, we have listed down the type of facets addressed by the selected publications given in Table 6. Type of research presented in the paper, its empirical type, the approach used and focused area has been inquired through RQ2 and listed in Table 6. As identified earlier, the research could be of evaluation type, solution type or experience type. In this mapping study, 23% of the research has presented a solution proposal to illustrate the novelty of the proposed solution for a problem or as an extension of an existing technique. 42% studies belonged to an evaluation type which represents the techniques has passed through the evaluation stages prior to its implementation or solutions have been evaluated after implementation. 22% of the mapping study presented experience
papers which showed the personal experience of the author about earthquake prediction techniques to be used in practice.

| Reference | Number of Records (EQ) | Accuracy | Magnitude Range | Data Set |
|-----------|------------------------|----------|-----------------|----------|
| [6]       | 60                     | 78%      | 5.2–7.7         | TS       |
| [9]       | 343 seismograms        | 99.71%   | ≥5.0            | TS       |
| [10]      | 47                     | 93.54%   | ≥5.5            | TS       |
| [13]      | 12 indices             | 91%      | ≥4.5            | TS       |
| [18]      | 9531                   | 69.8%    | ≥2.0            | ITS      |
| [20]      | 677245                 | 87.85%   | 3.6–9.1         | TS       |
| [21]      | 12690                  | 50.14%   | ≥3.0            | ITS      |
| [22]      | 522                    | 95.8%    | ≥4.0            | TS       |
| [23]      | 1773                   | 85.73%   | ≥3.5            | TS       |
| [24]      | 337                    | 63%      | ≥3.0            | ITS      |
| [38]      | 1000                   | 80.1%    | < 5.5           | TS       |
| [43]      | 227                    | 70%      | < 5.0           | TS       |
| [50]      | 77                     | 80.11%   | ≥5.0            | TS       |
| [55]      | 26481                  | 78%      | 2.5–7.5         | TS       |
| [63]      | 10567                  | 40%      | 0.1–5.9         | ITS      |
| [76]      | 100                    | 99.99%   | 5.5–7.7         | TS       |
| [86]      | 476                    | 87.2%    | ≥5.0            | TS       |
| [80]      | 248                    | 84%      | ≥5.5            | TS       |
| [83]      | 78                     | 88%      | ≥5.0            | TS       |
| [84]      | 1059846                | 86.28%   | ≥1.5            | TS       |

Empirically, the studies included in this systematic mapping study have been categorized into the survey, experiment and case study. 13% of the researchers have conducted surveys to study the already presented prediction models. 39% have conducted experiments on earthquake data retrieved from multiple seismic zones to make earthquake predictions and 32% have presented the case studies in which earthquake prediction task has been worked out using the data of specific areas. In this mapping study, the next type facet is the prediction approach which has been further categorized into model, method, guideline, framework and tool. 40% of the included researches have computational model for making earthquake predictions, 40%, researchers have proposed a method for earthquake prediction, 13% have given the guidelines for earthquake prediction, only 2% of the included studies have presented a framework for the earthquake prediction and analyzed earthquake prediction tools.

Last type facet of this mapping study is the target area that has been classified as regional and global. 75% of the included researches have been focused to a certain specific regional area where as 24% of the researchers have used global data to forecast earthquake. Figure 3 shows the number of publications (n) according to the type facets given in RQ2.

4.4. ES type and System Specific Key Aspects of Proposed ES

Three types of the proposed ES have been identified by RQ3 and presented in Figure 4. Fuzzy expert system (FES) has been proposed for making earthquake predictions by 29% of the studies. Neuro-Fuzzy expert system for making an earthquake prediction has been proposed by 11% of the studies. The rule based expert system has been proposed by 7% of the included studies. 36% of the articles have used
machine learning for earthquake prediction and 12% of the studies have used other computational approaches like index development or classifier calculation for earthquake prediction. In this mapping study RQ3 also deals with exploring other key aspects of the proposed ESs like input domain, input attributes and their types, data type, prediction logic and the prediction technique covering the use of computational supporting software or algorithm for performing earthquake prediction task. Input domain can be the earthquake parameters like magnitude, b-value, etc. or precursors calculated from real time earthquake data. In this mapping study, 51% researches have directly consumed earthquake parameters (listed as quake variables in Table 6) whereas 38% have studied precursors that serve as indicators for an upcoming devastating earthquake event.

Further, we have explored the type of above stated input attributes to analyze that whether predictions have been made by consuming single input attribute or combination of multiple attributes has been used for earthquake predictions. In this mapping study, 27%, researchers have made predictions on the basis of a single attribute where as 68% studies have used a combination of multiple input attributes for earthquake predictions. Through data type we have worked to find that input variables passed to the proposed ES are quantitative type (numeric form like magnitude, slope, etc.) or qualitative type (discrete form like water elevation, emission of radon gas etc.). It has been observed that 57% of researchers have used numeric inputs for earthquake forecast whereas 43% of the studies have performed the earthquake prediction task using a discrete type of input. This mapping study has also captured the data regarding prediction logic and prediction methodology. Through prediction logic, we have determined that the article have used the inductive or deductive logic for making earthquake predictions. Inductive logic has been used by 62% of the studies, whereas deductive logic has been presented in 32% of the included studies for giving absolute results. Next we have worked to determine the predictive methodology to describethe use of any software or an algorithm for evaluation of the proposed system. 42% of the studies have used multiple algorithms for evaluation of their predictions, 48% have used the MATLAB software for evaluation of the proposed ES and 10% have adopted other evaluation mechanisms.

4.5. Quality Assessment

The quality assessment score obtained by each paper has been presented in Table 6. These articles have been collected in three distinct categories and presented in Table 11 according to the scores obtained by every article given Table 6. By observing the quality scores, 74% of the papers included in the mapping study had obtained above average score, 11% of the studies had obtained average score and 15% of the studies remained below average. This quality assessment may facilitate researchers in the selection of articles for their work.

| Reference | Score Average | Total % |
|-----------|---------------|---------|
| [1–14,17,19–22,25–27,31,32,34,35,37–39,42–44,49–52,55,56,58–72,74] | Above average | 55 79 |
| [18,23,24,28,53,54,73] | Average | 7 10 |
| [15,16,30,33,36,40,41,57] | Below average | 8 11 |

5. Discussion

In this mapping study, main techniques used for earthquake prediction including rule-based, fuzzy, neuro-fuzzy and machine learning have been explored. Expert systems based approaches have been used for seismic risk assessment for landslide susceptibility through seismic hazard analysis [50–52] and soil classification [53]. ES have also been applied in earthquake engineering for seismic hazard analysis and assessment of bridges and buildings under multiple hazards [24,54,55]. The expert systems have been used to analyze multiple aspects of earthquake prediction, but due to the non-existence of the
time-dependent global earthquake forecasting model, the regional earthquake likelihood models have been popular [87]. On the other hand, some initial research has been conducted to design earthquake early-warning systems that work globally [32,49].

A detailed discussion regarding the history and theory of accelerating seismic release and preparedness for an earthquake has been conducted in [90,91]. Extended earthquake sequences with stable features have been observed over long time periods and explained accelerated seismicity before the occurrence of devastating earthquakes with in time. The aftershock decay models proposed in the articles from 1894 till 2014 about accelerating seismology, has been analyzed in [92] and valuable information about multiple scientific process including earthquake cascaded events have been collected. Multiple anomalies have been investigated in [93] to formulate the criteria for identification of the genuine precursors from a preliminary list of identifying precursors, methods or case studies.

A collection of one hundred articles related to accelerating seismology has been studied in [94] to classify the precursor into two types including critical processes such as cascading triggering of earthquake events or normal processes such as pressure on main fault. Many other studies investigated earthquake precursors like [95] examined multiple parameters collected from anomalies present in geophysical fields such as ionospheric disorder for short term earthquake prediction. Genetic algorithm (GA) has been used to optimize the hybrid artificial neural network model for the prediction of peak particle velocity in [96]. An artificial neural network has been applied to predict shear wave velocity in [97]. A seismic data-driven tool has been proposed for seismic fracture identification using large post-stack seismic dataset in [98]. The dynamic response of geogrid machine foundation bed has been studied in [99]. Rockfall hazard assessment using artificial neural network has been performed in [100]. The properties of the lower ionosphere have been examined in [101] using random matrix theory for the prediction of earthquakes. Both spatial and spatio temporal earthquake predictions have been made in [102] using machine learning methodologies. Reference [103] presented a natural time analysis of seismic-electric signal emerged before two earthquake events for the prediction of next expected earthquake events. The density of foreshocks and aftershocks has been analysed in [72] for prediction of future earthquakes that may occur in the selected seismically active regions.

Reference [56] examined the impact of deep learning algorithms for classification of earthquake precursors for extraction of seismic patterns and unique features from big data. Reference [57] distinguished between seismic signals and non seismic signals using logistic regression method on the data collected from National Seismological Network of Colombia. Reference [58] applied Support Vector regression and Hybrid neural Network for earthquake prediction in Hindukush, Chile and Southern California regions with prediction accuracy rate of 82.7%, 84.9%, 90.6% respectively. Reference [59] analyzed earthquake magnitude prediction on the basis of regression algorithms and cloud based big data infrastructure. Reference [60] used grid-search method to construct support vector machine (SVM) based model for earthquake prediction. Reference [61] launched a web based platform for automatic calculation of seismic hazard fields to predict earthquakes. Reference [62] highlighted the vital role of temporal strong ground motion parameters in earthquake engineering and risk assessment using machine learning methods. Reference [63] used gradient boosted trees algorithm of machine learning to perform fivefold cross validation on training data set from earthquake catalogs to make earthquake predictions.

References [64] developed an earthquake early warning system using image recognition techniques. Reference [65] studies multiple machine learning methods including random forest, artificial neural network, recurrent neural network, Naive Bayesian and regression for earthquake prediction. Reference [66] examined the efficiency of bio-inspired algorithms for supervised classification of on real datasets to handle emergencies. Reference [67] discussed the emerging Regional Earthquake likelihood models in making earthquake predictions with improved accuracy. Reference [68] used tree-based ensemble methodologies for earthquake prediction within time period of 15 days and calculated seismic features of Hindukush region applying machine learning methods for macro earthquake prediction. Reference [69] proposed a multi-step prediction method for short-term prediction of strong
earthquake with relatively high accuracy. Reference [70] proposed a monitoring system for preparing machine learning data-sets for earthquake prediction based on seismic-acoustic signals from stations in Azerbaijan.

Reference [71] estimated the magnitudes of earthquake events recorded on daily bases using artificial neural network (ANN) to prove that training set of global data is more effective in earthquake prediction than making earthquake prediction using local data. References [72,73] studied the importance of machine learning methods in earthquake prediction and highlighted the impact of accurate prediction on country’s economy. Reference [74] presented a scheme for large earthquake prediction based on radial basis function (RBF) neural network (NN) models.

This section summarizes and discusses the results of the systematic mapping study. Taxonomy of earthquake prediction is given in Figure 5.

There are two distinct types of earthquake prediction approaches presented in Figure 5, i.e., deterministic forecasts and probabilistic forecasts. Deterministic forecasts are made on the base of earthquake characteristics like rupture length, modified Mercalli and return period whereas probabilistic forecasts deals with precursors, implications of earthquake physics and elastic rebound. Table 12 clusters the articles according to the taxonomy given in Figure 5.

From Table 12 it is clear that multiple approaches have been used for earthquake prediction including Rule based, Fuzzy and Neuro-fuzzy and machine learning. For deterministic estimations, earthquakes have been grouped according to their magnitude range by applying classification, clustering and machine learning techniques. For probabilistic forecasts, multiple artificial intelligence methods have been exercised for making earthquake predictions. Comparative studies have been conducted [13], systematic methods of predicate logic have also been applied to analyze the precursor that may have vital importance for earthquake prediction \[9,27,32,57,65\]. To estimate the mutual relationship of precursors, regression line has been calculated [26]. Machine learning approaches have shown greater improvement in prediction accuracy presented in Table 10. Multi criteria decision making (MCDM) approaches including Technique for order of preference by similarity of ideal solutions (TOPSIS) and
Aggregated indices randomization (AIRM) have also been applied for earthquake prediction. Multiple precursors may occur before catastrophic earthquakes which have been analyzed through MCDM methods by assigning weightage to every precursor for the prediction of expected earthquake events. Pattern recognition techniques have also been exercised to analyse the seismic patterns generated by the energy released in previous earthquakes and radon emission recorded before an earthquake.

Table 12. Approaches used to predict particular seismic phenomena.

| Domains                      | Seismic Phenomena                  | Approach                                      | Reference                                                                 |
|------------------------------|------------------------------------|-----------------------------------------------|---------------------------------------------------------------------------|
| Deterministic                |                                     |                                               |                                                                           |
| Characteristic              | Rupture length Modified Mercalli    | Classification, Clustering, Machine Learning  | [2,6,10,16–20,28,33–35,37,39,42,44,58–62,65,69,70,72,74,80,86]            |
| earthquake                  | Return Period                       | Neural network (NN)                           |                                                                           |
| Probabilistic               |                                     |                                               |                                                                           |
| Precursor                   | Animal behavior                     | Predicate Logic, Aggregated Indices Randomization | [27,66]                                                                    |
|                             | Seismic velocity                    | Regression                                     | [9,32,57]                                                                 |
|                             | Seismic resistivity                 |                                               |                                                                           |
|                             | Topography uplift                   |                                               |                                                                           |
|                             | Radion emission                     | Comparison, Clustering, ML, NN                | [21,50,77]                                                                |
|                             | Seismic electric signal             |                                               |                                                                           |
|                             | Electromagnetic signals             |                                               |                                                                           |
|                             | Ground water elevation              |                                               |                                                                           |
|                             | Land sliding                        |                                               |                                                                           |
| Earthquake physics          | Earthquake light                   | ML, NN Technique for Order of Preference by Similarity to Ideal Solution | [36,85]                                                                  |
|                             | Ionosphere disorder                 |                                               |                                                                           |
| Elasticbound                | Seismic Gap                         | Patterns recognition                          | [37,38,40,91]                                                            |
|                             | Seismic Pattern                     | Clustering, ML                                | [49,68]                                                                  |

5.1. Comparative Analysis of Methods

Multiple techniques have been used for earthquake prediction in the literature. We have formulated the foundation of this mapping study on expert systems. However, there are many other approaches as well for the prediction of earthquake presented in the literature. We have compared expert system developed for earthquake prediction with other artificial intelligence techniques used for the same in Table 13.

Table 13. Comparison of three Artificial intelligence techniques.

| Method                        | Comparison                                                                 |
|-------------------------------|---------------------------------------------------------------------------|
| Neural networks and Expert systems | Expert system is about capturing and encoding (often manually) rules that experts use so as to develop a program that can mimic their behavior in a very specific domain. It often involved chaining these rules together. With ANN the rules are encoded automatically by presenting examples, good and bad, to the network. The network adjusts weightings over many iterative cycles, honing its output to the correct value. Feed Forward Neural Networks can predict long term and short term earthquakes but it cannot get feedback of output from multiple layers and Back Propagation Neural Network mostly trapped in different local conditions during the training phase of earthquake data sets. However, probability of getting desired output raises when it is tested with ideally designed inputs. |
| Machine learning and Expert systems | Machine learning (ML) focuses on modeling of data statistically and expert is involved at the time of decision. Supervised learning algorithms are used to copy the ending decisive behavior of the Expert systems are based upon set of rules prescribed by human expert and learn by directly injecting the domain level knowledge of human expert. The knowledge obtained from the expert is completely converted into membership functions and used in decision making. Explanation facility is also available as an expert describes all the steps till decision, the basis and exception handling procedures. A rigid system is developed that follows exact rules as described by the expert. Rigidness of the expert system makes it most suitable from all other techniques for predicting future earthquakes. |

Table 14 presented the comparison of multiple methods including fuzzy, neuro fuzzy, rule based and machine learning used for earthquake prediction in the literature. It can be observed that both deterministic and probabilistic methods are being exercised for earthquake prediction. Many researchers have performed numerical experiments to achieve success in predicting earthquakes. Some have developed tools while others have explored multiple dimensions of application area.

Table 14 clearly presents that most recent studies have worked on exploring machine learning based models for earthquake prediction.
| Method                          | Ref. | Prediction Approach | Algorithm Defined | Application Area   | Dataset   |
|--------------------------------|------|---------------------|-------------------|--------------------|-----------|
| Fuzzy Expert System            |      |                     |                   |                    |           |
|                                | [2]  | ✓                   | ✓                 | ✓                  | ✓         | China     |
|                                | [6]  | ✓                   | ✓                 | ✓                  | ✓         | Iran      |
|                                | [8]  | ✓                   | ✓                 | ✓                  | ✓         | Taiwan    |
|                                | [9]  | ✓                   | ✓                 | ✓                  | ✓         | Iran      |
|                                | [10] | ✓                   | ✓                 | ✓                  | ✓         | California |
|                                | [13] | ✓                   | ✓                 | ✓                  | ✓         | China     |
|                                | [14] | ✓                   | ✓                 | ✓                  | ✓         | Caraga    |
|                                | [15] | ✓                   | ✓                 | ✓                  | ✓         | Turkey    |
|                                | [18] | ✓                   | ✓                 | ✓                  | ✓         | Nepal     |
|                                | [21] | ✓                   | ✓                 | ✓                  | ✓         | China     |
|                                | [23] | ✓                   | ✓                 | ✓                  | ✓         | India     |
|                                | [24] | ✓                   | ✓                 | ✓                  | ✓         | India     |
|                                | [26] | ✓                   | ✓                 | ✓                  | ✓         | Nepal     |
|                                | [50] | ✓                   | ✓                 | ✓                  | ✓         | China     |
|                                | [51] | ✓                   | ✓                 | ✓                  | ✓         | Saudi Arabia |
|                                | [52] | ✓                   | ✓                 | ✓                  | ✓         | Malaysia  |
|                                | [80] | ✓                   | ✓                 | ✓                  | ✓         | Iran      |
|                                | [82] | ✓                   | ✓                 | ✓                  | ✓         | Iran      |
|                                | [83] | ✓                   | ✓                 | ✓                  | ✓         | Malaysia  |
|                                | [84] | ✓                   | ✓                 | ✓                  | ✓         | Ethiopia  |
|                                | [86] | ✓                   | ✓                 | ✓                  | ✓         | Iran      |
|                                | [17] | ✓                   | ✓                 | ✓                  | ✓         | Chile     |
|                                | [19] | ✓                   | ✓                 | ✓                  | ✓         |          |
|                                | [20] | ✓                   | ✓                 | ✓                  | ✓         |          |
| Method                    | Ref. | Prediction Approach | Algorithm Defined | Application Area | Dataset |
|--------------------------|------|---------------------|-------------------|------------------|---------|
|                          |      | Deterministic       | Probabilistic     | Global Approximation | Numerical Experiment | Exploration with actual forecasts | Success Achieved | Characteristic Earth quake | Precursors | Zone Studied |
|                          |      |                     |                   |                  |                     |                                   |                |                           |            |             |
| **Neuro Fuzzy Expert System (NFES)** |      |                     |                   |                  |                     |                                   |                |                           |            |             |
|                          | [22] | ✓                   |                   |                  |                     | ✓                                  | ✓               | ✓                          | ✓          | Iran         |
|                          | [27] | ✓                   |                   |                  |                     |                                  |                |                           | ✓          |             |
|                          | [28] | ✓                   |                   |                  |                     |                                  |                |                           | ✓          | Iran         |
|                          | [30] | ✓                   |                   |                  | ✓                  | ✓                                  |                |                           | ✓          |             |
|                          | [32] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [33] | ✓                   |                   |                  |                     |                                  |                |                           | ✓          | Turkey       |
|                          | [49] | ✓                   | ✓                 | ✓                | ✓                  |                                   |                |                           | ✓          | China        |
|                          | [77] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [81] | ✓                   | ✓                 |                  |                     |                                  |                |                           | ✓          | Greece       |
| **Machine Learning (ML)** |      |                     |                   |                  |                     |                                   |                |                           |            |             |
|                          | [34] | ✓                   |                   |                  |                     |                                  |                |                           |            | Cyprus       |
|                          | [35] | ✓                   |                   |                  |                     |                                  |                |                           |            | India        |
|                          | [36] | ✓                   |                   |                  |                     |                                  |                |                           |            | India        |
|                          | [37] | ✓                   |                   |                  |                     |                                  |                |                           |            | Iran         |
|                          | [38] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [39] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [40] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [41] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [42] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [44] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [56] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [57] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [58] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
|                          | [59] | ✓                   |                   |                  |                     |                                  |                |                           |            |             |
Table 14. Cont.

| Method                  | Ref. | Prediction Approach | Algorithm Defined | Application Area | Dataset |
|-------------------------|------|---------------------|-------------------|------------------|---------|
|                         |      | Deterministic       | Probabilistic     | Global Approximation | Numerical Experiment | Exploration with actual forecasts | Success Achieved | Characteristic Earth quake | Precursors | Zone Studied |
|                         |      | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Japan        |
|                         | [60] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Japan        |
|                         | [61] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Croatia      |
|                         | [62] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Iran         |
|                         | [63] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Turkey       |
|                         | [64] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Greece       |
| Machine Learning (ML)   | [65] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Pakistan     |
|                         | [66] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Chile        |
|                         | [68] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Chile        |
|                         | [69] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Chile        |
|                         | [70] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Chile        |
|                         | [71] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Chile        |
|                         | [72] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Chile        |
|                         | [74] | ✓                   | ✓                 | ✓                | ✓                  | ✓                         | ✓               | ✓                         | ✓          | Chile        |
5.2. Principal Findings

The goal of this systematic mapping study is to examine the current status of ES used to predict earthquakes by selecting the appropriate number of recently published papers. We have passed all the studies from our selection and quality criteria to classify the studies according to the scores obtained by every research work on the basis of rules listed in Table 6. The categories of the studies according to their quality scores has been listed in Table 6. In this mapping study, 74% articles have above average scores, 15% articles scored average quality results and 11% researches are below average. Table 11 will facilitate the researchers in selecting quality studies.

In Figure 6, we have combined the answers from sub-parts of RQ2 for presenting an overview of earthquake prediction activity. This mapping has allowed us to obtain more information on how the results from each RQ relate to each others. Figure 6 presents the research type facet related to earthquake prediction, distributed over approaches and its empirical type. It allows us to conclude that only one model was proposed by the authors that mainly report their experience in the earthquake prediction process. However, guidelines have been provided by six authors. The majority of the solution proposals have developed models for earthquake prediction. However, just one researcher has developed a tool for earthquake prediction evaluation. Further information regarding the relationship between type facets is shown in Figure 6.

![Figure 6. Relationship between type facets given in Research Question 2 (RQ2).](image)

RQ3 deals with identification of the type of proposed ES. Figure 7 shows the relationship between the proposed ES with other system specific details. Machine/deep learning has emerged as most focused and recent trend in the earthquake prediction process. However, it can be clearly seen from Figure 7 that FES has been proposed by a majority of the researchers for a long time period. FES is representing a balance in the selection of all input parameters except the use of deductive logic in earthquake prediction in Figure 7. It might be due to the nature of FES basically reflecting uncertainty [15] that’s why most of the researchers have used inductive logic to propose FES for the earthquake prediction. However, some of the researchers have also worked to proposed NFES and RBES but their frequency is very low.
Globally, we need a program of identification and characterization of potentially hazardous faults in multiple seismic zones. From those studies, site-specific expected seismic shaking maps can be developed that would facilitate in developing expert system for earthquake prediction process.

Activities focusing on comparative testing of computational prediction methods based on seismicity and fault information that provide probabilistic predictions of moderate magnitude earthquakes on a geographic grid are needed. This approach can be optimized to achieve useful statistics in a short time and can also advance the research field by providing insights into the computational predictability of earthquakes. However, visible hypotheses such as the M8/MSc predictions of global earthquakes, the “reverse detection of precursors” method, or the Retrograde Intravenous Pressure Infusion “RIPI” method, each of which analyze temporal and spatial variations in seismicity, or other methods based on observable quantities such as the electromagnetic field, ground temperature, gaseous emissions, geodetic deformation, or changes in seismic wave speed. Many of the most visible and influential earthquake predictions are posed as “alarms” or “times of increased probability” (TIPs) within some specified region rather than as probabilities on a grid of points.

Evaluation of emerging situations such as earthquake swarms, the likelihood of damaging aftershocks or triggered earthquakes following major quakes, or the likelihood of re-rupture of a fault following a major earthquake should be examined. Likewise, a broader suite of statistical tests, spanning the range from straightforward to sophisticated, would allow some prediction methods to be easily disproven in a way that’s clear to researchers, the media and the public, while providing the rigorous analysis required for comparative testing. These should include statistical tests applicable to alarm-based computational prediction methods.

The findings of our systematic mapping study have the following implications for practitioners and researchers. This study will allow them to discover the existing use of expert system in the literature concerning earthquake prediction.

In order to improve the reliability in earthquake prediction, researchers and practitioners may consider the following advices:

1. Globally, we need a program of identification and characterization of potentially hazardous faults in multiple seismic zones. From those studies, site-specific expected seismic shaking maps can be developed that would facilitate in developing expert system for earthquake prediction process.
2. By comparing different forecasts that are computed from common data, contrasts in performance can be tied to specific features of the computational prediction method. Enforcing the need to create a testable prediction, hypothesis that may reveal shortcomings or incomplete features of the prediction method is needed.
3. Activities focusing on comparative testing of computational prediction methods based on seismicity and fault information that provide probabilistic predictions of moderate magnitude earthquakes on a geographic grid are needed. This approach can be optimized to achieve useful statistics in a short time and can also advance the research field by providing insights into the computational predictability of earthquakes. However, visible hypotheses such as the M8/MSc predictions of global earthquakes, the “reverse detection of precursors” method, or the Retrograde Intravenous Pressure Infusion “RIPI” method, each of which analyze temporal and spatial variations in seismicity, or other methods based on observable quantities such as the electromagnetic field, ground temperature, gaseous emissions, geodetic deformation, or changes in seismic wave speed. Many of the most visible and influential earthquake predictions are posed as “alarms” or “times of increased probability” (TIPs) within some specified region rather than as probabilities on a grid of points.
4. Evaluation of emerging situations such as earthquake swarms, the likelihood of damaging aftershocks or triggered earthquakes following major quakes, or the likelihood of re-rupture of a fault following a major earthquake should be examined. Likewise, a broader suite of statistical tests, spanning the range from straightforward to sophisticated, would allow some prediction methods to be easily disproven in a way that’s clear to researchers, the media and the public, while providing the rigorous analysis required for comparative testing. These should include statistical tests applicable to alarm-based computational prediction methods.
5.3. Evolution of Tools and Techniques

To reveal the development trend of researchers, various tools and techniques used to develop ES for earthquake prediction have been listed in Table 10. It is clear from Table 10 that 41% of the researchers have used the MATLAB software for development of an ES. MATLAB is in the market since 1984. MATLAB is used for multi domain purposes like signal processing, image processing and automation, etc. It has Simulink, state flow, embedded coder and Simulink coder. Simulink facilitates the model based development where as code is automatically generated through embedded coder. Moreover, traceability of the code is much easier than legacy coding. Simulink helps in the development of a system in block diagrams by providing many elements like transfer function, summing junction, function generators and oscilloscopes which makes the work easier for the researchers. Through its debugging option, it has gained the trust of the researchers from last thirty five years. It is also clear from Table 6 that for earthquake prediction rule-based expert systems have been focused till 2013 then, till 2017 fuzzy and neuro-fuzzy expert systems have been explored. But, now a prominent change in the research trend has been observed from 2018 onwards that earthquake predictions are being carried out using machine learning and deep learning approaches. Changing trend of earthquake prediction approaches has been shown in the timeline presented in the Figure 8.

![Timeline of earthquake prediction approaches](image)

**Figure 8.** Timeline of earthquake prediction approaches.

6. Conclusion and Future Directions

This paper has presented a systematic mapping study to summarize the existing research on multiple approaches involving machine learning, neuro-fuzzy, fuzzy and rule based approaches that have been used for earthquake prediction. Out of 2137 studies, 70 articles published between January 2010 till January 2020 were carefully selected and classified on the basis of research type, empirical type, approach, target area, and other system specific parameters. Publication source and trend have also been identified. Most of the articles considered in this study have been selected from peer reviewed journals and (Computing Research and Education) CORE ranked conferences. Majority of the papers included in this mapping study involve empirical validation for the proposed solutions to predict earthquakes.

The use of various types of ES presented in this study may help researchers to identify approaches that can be adopted in order to improve the quality of earthquake prediction in their work. For future research more attention should be given to the application of machine learning and deep learning methods for earthquake prediction. Due to ever increasing volume of data, there is a need to employ machine learning and deep learning for the prediction of earthquakes. Moreover, there is a need to conduct more of evaluation research for the validation of the already presented prediction models based on fuzzy logic.

The analysis of the presented research works show that most of the approaches focused on analyzing the precursors generating direct warning of an earthquake. However, recent trends show that there is a need to extend this work by involving other factors which may include volcanic eruption, nuclear explosion, hurricanes, tsunamis etc.

The results obtained showed that an increasing amount of attention has been paid to the use of an ES for earthquake prediction since 2011. It has been noticed that till 2013 the research has been more focused on rule based methods for earthquake prediction. Then the trend has changed towards using fuzzy and neuro fuzzy methods till 2018. Machine learning and deep learning has emerged as the most focused approach for earthquake prediction in the recent time.
The classification developed in this mapping study has presented increased trend of applying FES and ML in making long term earthquake predictions. However, in the future, more advanced deep learning based model should be designed to make pinpoint predictions. Moreover, there is a continuing need to develop a suite of basic tools and reference models to rapidly establish an unbiased framework to evaluate prediction methods, which enforces strict adherence to the scientific method, motivates investigators to accurately and unambiguously express prediction hypotheses, and provides guidance and tools for formal testing of those hypotheses. These features would lead to progress in evaluating seismicity-based models.

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