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Review

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Review

Applying Machine Learning to Earthquake Engineering: A Scientometric Analysis of World Research

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Abstract: Machine Learning (ML) has developed rapidly in recent years, achieving exciting advancements in applications such as data mining, computer vision, natural language processing, data feature extraction, and prediction. ML methods are increasingly being utilized in various aspects of seismic engineering, such as predicting the performance of various construction materials, monitoring the health of building structures or components, forecasting their seismic resistance, predicting potential earthquakes or aftershocks, and evaluating the residual performance of post-earthquake damaged buildings. This study conducts a scientometric-based review on the application of machine learning in seismic engineering. The Scopus database was selected for the data search and retrieval. During the data analysis, the sources of publications relevant to machine learning applications in seismic engineering, relevant keywords, influential authors based on publication count, and significant articles based on citation count were identified. The sources, keywords, and publications in the literature were analyzed and scientifically visualized using the VOSviewer software tool. The analysis results will help researchers understand the trending and latest research topics in the related field, facilitate collaboration among researchers, and promote the exchange of innovative ideas and methods.

Keywords: machine learning; seismic engineering; pre-earthquake design; earthquake prediction; post-earthquake evaluation

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1. Introduction

Earthquakes stand as one of the most devastating natural catastrophes worldwide, encompassing the potential to induce extensive human casualties, psychological trauma, and substantial economic setbacks due to both immediate and secondary effects. Efforts by researchers across the globe to curtail the detrimental impacts of earthquakes have remained ceaseless. Particularly in the era since the commencement of the 21st century, the advancement of the second generation of performance-based seismic engineering has notably elevated the seismic resistance of architectural structures on an international scale [1]. However, in comparison to other fields, despite the industrialized nature of structural seismic design and post-earthquake assessment engineering, the level of mechanization, automation, intellectualization, and incorporation of information technology within infrastructure has remained relatively underdeveloped [2,3].

Since its inception in the 1940s, Artificial Intelligence (AI) has found applications across numerous disciplines, culminating in the establishment of diverse algorithms [4–8]. With the rapid advancement of Machine Learning (ML), notably Deep Learning (DL) [9] since 2006, AI has emerged as a focal point of research and application across various fields. ML is a multidisciplinary field involving probability theory, statistics, approximation theory, convex analysis, algorithmic complexity theory, and more. Among the current definitions of ML, the most cited is as follows: A computer program is said to learn from experience

E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E [10]. It focuses on how computers simulate or implement human learning behaviors to acquire new knowledge or skills, reorganize existing knowledge structures, and continuously improve performance. It is at the core of artificial intelligence, serving as the fundamental approach to endow computers with intelligence, with applications spanning various domains of AI. ML has actually been around for decades, or one could argue even centuries. Tracing back to the 17th century, developments such as Bayes and Laplace's derivation of least squares and Markov chains laid the groundwork for tools widely used in machine learning. However, the rapid expansion of machine learning began in the mid-20th century, from the late 1970s to the mid-1980s, also known as the renaissance of machine learning. During this period, the focus shifted from learning individual concepts to learning multiple concepts and exploring various learning strategies and methods. As the field of machine learning has progressed, academic activities related to it have become unprecedentedly active. Driven by big data, machine learning technologies are now permeating various industries.

Globally, nations are vigorously promoting industrial transformation, amalgamating the new generation of information technology with modern manufacturing and productive service sectors. Some scholars regard ML technology as a potential solution to address the overreliance on empirical data and limited intelligence in earthquake engineering [11–13]. AI is poised to infiltrate all facets of human societal and productive activities, profoundly shaping the future trajectory of seismic engineering. Within seismic engineering, labor-intensive tasks such as structural seismic design and demanding endeavors in adverse environments like post-earthquake surveys and assessments are envisaged to be supplanted by machines or robots. This perspective has garnered increasing acknowledgment among numerous scholars within the seismic engineering field [14–16]. Currently, ML technologies have been applied in seismic engineering, demonstrating some practical applications and proving their reliability. For instance, after the 7.8 magnitude earthquake in Turkey, Dutch scholar Frank Huibers tweeted a warning on February 3rd, indicating a potential earthquake of magnitude 7.5 or above in the area. Just three days later, this AI-based prediction was validated. The China Earthquake Networks Center has developed a seismic reporting robot based on artificial intelligence technology. This robot autonomously generates reports, providing detailed information on earthquake parameters, epicenter topographic maps, surrounding population data, nearby village locations, county and district positions, historical earthquake data in the affected area, epicenter summaries, and weather forecasts for the next three days within seconds after an earthquake occurs. This system possesses robust data storage and spatial analysis capabilities and utilizes massive datasets for network retrieval, offering significant support for earthquake evacuation, rescue operations, and secondary disaster prevention. In post-earthquake rescue efforts, unmanned aerial vehicles and quadruped robots manufactured based on computer vision technology have greatly facilitated search and rescue operations for survivors.

In recent years, propelled by advancements in artificial intelligence technology, ML techniques have progressively permeated various fields of seismic engineering. Across fields such as pre-earthquake design [17–21], earthquake prediction [22–26], and post-earthquake assessment [27–31], a plethora of diverse ML algorithms have been increasingly employed, yielding a range of achievements and associated tools. Concurrently, the swift evolution of technology may pose information constraints to scientists, impeding innovative research and scholarly collaboration [32], thus necessitating a comprehensive review of existing studies. The objective of this paper is to conduct a bibliometric investigation of literature published in the past decade (2013–2023) that pertains to the application of ML in seismic engineering. To achieve this, VOSviewer (1.6.19), a scientometric assessment tool for constructing and visualizing networks of scholarly metrics, is employed. These networks could encompass publications, keywords, or authors and are constructed based on bibliographic coupling, keyword co-occurrence, or co-citation relationships. Unlike traditional literature review approaches, scientometric evaluation methods exhibit characteristics of comprehensive information content, ease of comprehension, and facilitation of multifaceted analysis. This study is poised to facilitate a precise understanding for researchers in pertinent fields regarding prominent research fields and recent trends in the application of ML technology within seismic engineering. Through graphical and statistical representations of researchers and nations, this research further fosters academic cooperation and the exchange of innovative concepts and technologies.

2. Review Strategy

In this study, a bibliometric analysis of literature data was conducted. Bibliometrics is a data analysis technique that quantifies numerous features of a large body of literature and facilitates scientific visualization [33–36]. To employ this technique, reliable search engines must be utilized. Web of Science and Scopus are two highly accurate databases that are well-suited for the purpose of this study [37–41]. Considering that Scopus is strongly recommended by numerous scholars for bibliometric analyses [42–46], the present paper employed the Scopus database to gather and refine the required literature information. To select relevant literature in the field of ML applied to engineering seismic studies, the authors employed the keywords depicted in Table 1 for retrieval, yielding a preliminary total of 3189 results. Keywords for different subfields were connected using the "OR" operator, such as "machine learning* concrete* OR machine learning* steel*". Additionally, the "NOT" search operator was utilized to mitigate overlap between distinct subfields; for example, when searching for literature related to predicting concrete material properties, commands like "NOT joint" were employed to exclude literature related to concrete joints, which should be categorized under the subfield of structural and component performance assessment. Furthermore, extensive filtering criteria were applied to eliminate irrelevant literature. For instance, when retrieving literature related to material property prediction, the subject category was confined to engineering and materials science. Additionally, the authors meticulously screened the sources of retrieval. For instance, among the 160 sources mentioned in the search results related to material property prediction, 84 sources with lower relevance were excluded from consideration.

Table 1. Keywords used for the literature search and the number of retrieved articles.

Research Field	Subdivision	Keywords	Results
Pre-earthquake design	Material property prediction	Concrete; steel; wood; timber; machine learning	1224
	Structure performance evaluation	Column; beam; joint; frame; building; machine learning	1310
Earthquake prediction	Mainshock prediction	Earthquake; mainshock; machine learning	555
	Aftershock prediction	Aftershock; machine learning	44
Post-earthquake assessment	Damage identification	Earthquake; damage; machine learning	17
	Residual performance evaluation	Earthquake; evaluation; assessment; machine learning	39

This study employed VOSviewer for the scientific visualization and quantitative assessment of the collected literature data. VOSviewer is an opensource plotting tool available for free and is widely utilized across diverse research fields, with extensive endorsement by numerous scholars [47–49]. Prior to conducting the analysis, several analytical parameters within VOSviewer required specification. For instance, the minimum occurrence value for keywords was set at 15 to mitigate the generation of an excessive number of sources, thereby ensuring the readability of the generated mappings. Throughout the process of bibliometric analysis of the literature data, the authors conducted evaluations of various aspects, including the frequency of keyword occurrences, the most prolific authors, the most cited references, and the extent of national involvement. The study also encompassed the description of multiple characteristics, their interrelations, and co-occurrence phenomena.

3. Results Analysis

3.1. Pre-Earthquake Design

3.1.1. Literature Publication

This analysis is based on the subject classifications provided by Scopus, as depicted in Figure 1. Engineering, Materials Science, and Computer Science were identified as the top three subject fields within the retrieved literature, accounting for 52.2%, 18.2%, and 6.5% of the total literature, respectively, and contributing to a combined total of 76.9% of the literature. As evident from Figure 2, the number of published papers has shown a significant increasing trend over the years, particularly after 2017. As of 2023, the total count of publications related to pre-earthquake design and ML has reached 2534, indicating the widespread integration of ML techniques in predicting material properties and evaluating component and structural capabilities. This significantly reduces the need for experimental procedures and offers a faster and more cost-effective approach for the construction sector.

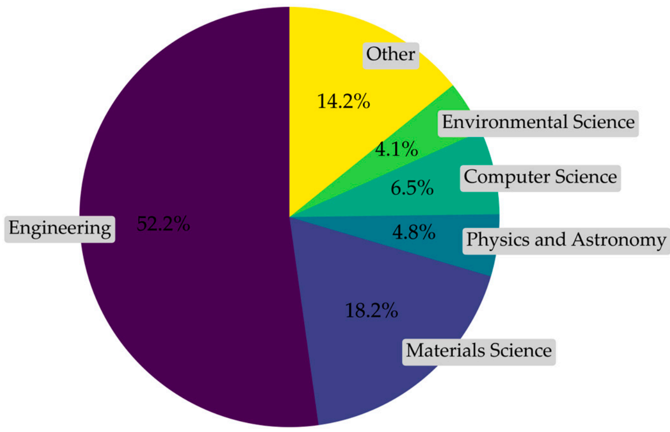

Figure 1. Relevant subject areas for articles from 2011 to 2023.

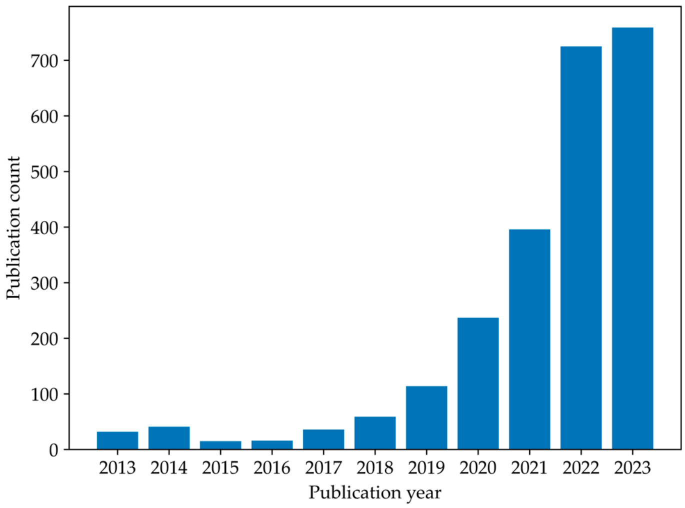

Figure 2. Annual publication trend for articles from 2011 to 2023.

Figure 3 depicts the quantity of literature related to the application of ML in pre-earthquake design published by different countries or regions and showcases the collaborative relationships among them. Within Figure 3, the minimum number of papers attributed to a single country or region is constrained to 10, with 42 countries or regions meeting this threshold. In Figure 3, the size of the circle corresponding to a country or region increases with the number of papers published by that entity. The United States, China, and India lead in article counts, contributing 708, 421, and 180 papers, respectively. Furthermore, the United States and China hold the highest citation counts for their papers, with 10,077 and 9539 citations, respectively. Figure 3 also reveals collaborations among scholars from different countries or regions, where circles of similar and proximate colors indicate increased collaborative activity. The graphical representation and quantitative documentation of participating countries will aid young scientists in establishing scientific partnerships, initiating collaborative endeavors, and exchanging innovative methods and concepts.

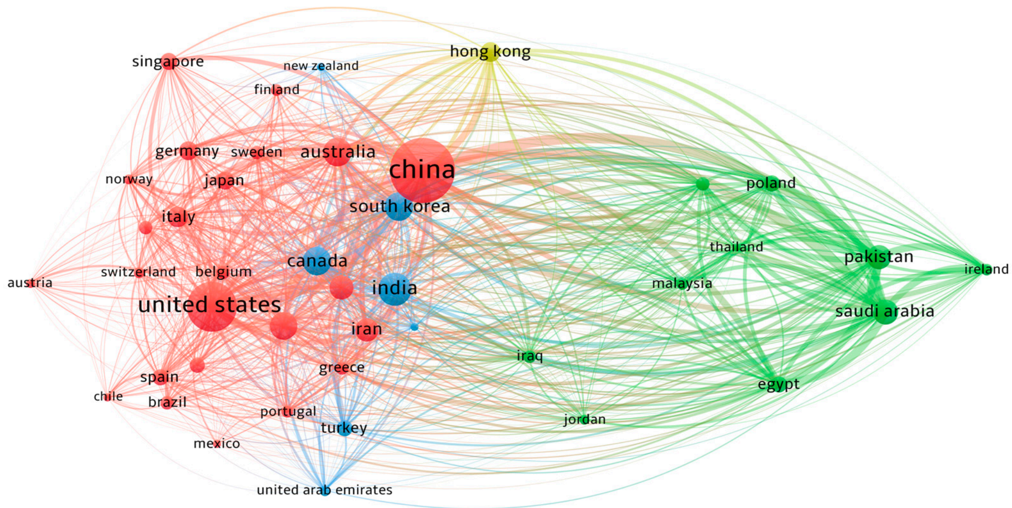

Figure 3. Systematic map of countries that presented a minimum of 10 articles.

3.1.2. Publication Sources

Tables 2 and 3 present the top five publishers with the highest number of publications as of 2023 as well as the top five publishers with the highest citation counts during this period. *Construction and Building Materials*, *Engineering Structures*, and *Journal of Building Engineering* were the top publication journals with 197, 196, and 142 papers, respectively. In addition, between 2013 and 2023, *Construction and Building Materials*, *Engineering Structures*, and *Automation in Construction* were cited the most, with 5145, 4017, and 3335 citations, respectively.

Table 2. Top 5 most published journals as of 2023.

S/N	Source Name	Total Publications	Total Citations
1	*Construction and Building Materials*	197	5145
2	*Engineering Structures*	196	4017
3	*Journal of Building Engineering*	142	1946
4	*Structures*	129	1130
5	*Materials*	119	1671

Table 3. Top 5 most cited journals as of 2023.

S/N	Source Name	Total Publications	Total Citations
1	*Construction and Building Materials*	197	5145
2	*Engineering Structures*	196	4017
3	*Automation in Construction*	89	3335
4	*Building and Environment*	97	2481
5	*Energy and Buildings*	65	2051

Figure 4 illustrates the visualization of sources that have published a minimum of 20 articles. Each circle in the figure represents a publishing source, and the size of the circle corresponds to the influence of that source on the current research areas, with larger circles indicating greater impact. As can be seen from the figure, *Construction and Building Materials*, *Engineering Structures*, and *Journal of Building Engineering* are the most influential journals. Sources with similar colors in the figure are more likely to be cited in the same article. The shorter and thicker the lines connecting the sources are, the closer their relationship is. For instance, the correlation between *Materials* and *Buildings* is stronger than that between *Materials* and *Journal of Building Engineering*.

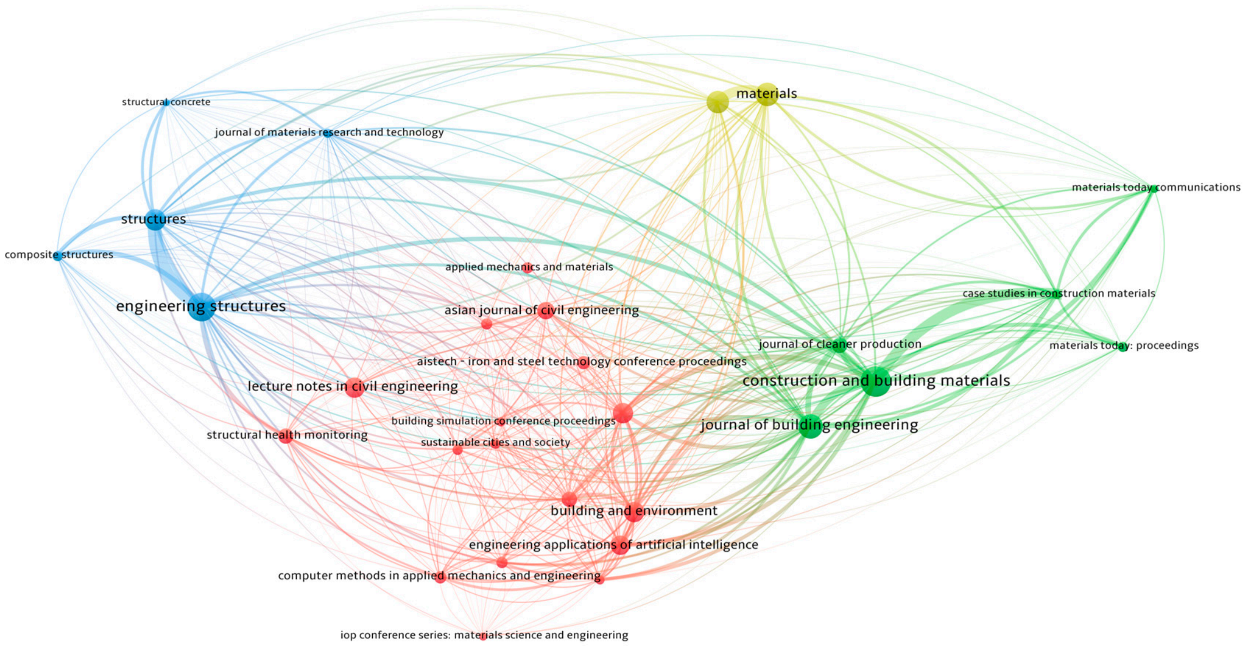

Figure 4. Systematic map of sources that published a minimum of 20 articles.

3.1.3. Keywords

Keywords play a crucial role in research as they differentiate and highlight the fundamental themes of a research field [50]. Table 2 records the top 20 frequently used keywords in the published literature. The five most recurrent terms in the subject field of the research are ML, prediction, learning systems, compressive strength, and learning algorithms. Notably, the term "learning systems" holds a remarkably high frequency of occurrence. It was formally defined during the SysML academic conference held at Stanford University in 2019 [51], while the other four keywords have been present since earlier stages. According to SysML, a learning system is defined as a class of systems designed and implemented in the real world to support the deployment of ML models. Thus, designing systems or programs to advance the practical application of ML algorithms emerges as a research hotspot and trend. In this context, in recent years, within the realm of studies utilizing ML algorithms for predicting material properties or structural responses, many researchers have inclined towards providing readers with concise and tangible procedures [52,53].

Figure 5 illustrates a keyword co-occurrence and connectivity-based system graph. Each circle in Figure 5 represents a keyword, with larger circles indicating higher frequency of occurrence. Furthermore, lighter-colored circles suggest that the corresponding keywords tend to appear in more recent literature, implying the emergence of novel research subjects. When two keywords are linked by a straight line, it signifies their simultaneous appearance within the same study. From Table 2 and Figure 5, it becomes evident that the most widely applied domain for machine learning techniques is the prediction of compressive strength in concrete. Currently, the prediction techniques for common concrete properties (compressive strength, elastic modulus, slump, carbonation depth, etc.) have become comprehensive and mature. By observing the lighter-colored circles in Figure 5, it is apparent that in recent years, aside from regular concrete, scholars have increasingly applied machine learning techniques to topics such as fly ash concrete, recycled concrete, and silica fume concrete. At the component and structural level, machine learning techniques are most frequently employed in structural health monitoring and structural response prediction. In Figure 5, various types of machine learning algorithms are the most frequently occurring keywords. From Table 4, it is evident that neural networks, decision trees, and support vector machines are the most widely applied machine learning algorithms. Some recently developed algorithms are used less frequently; however, they hold the potential to further enhance the accuracy of existing prediction models.

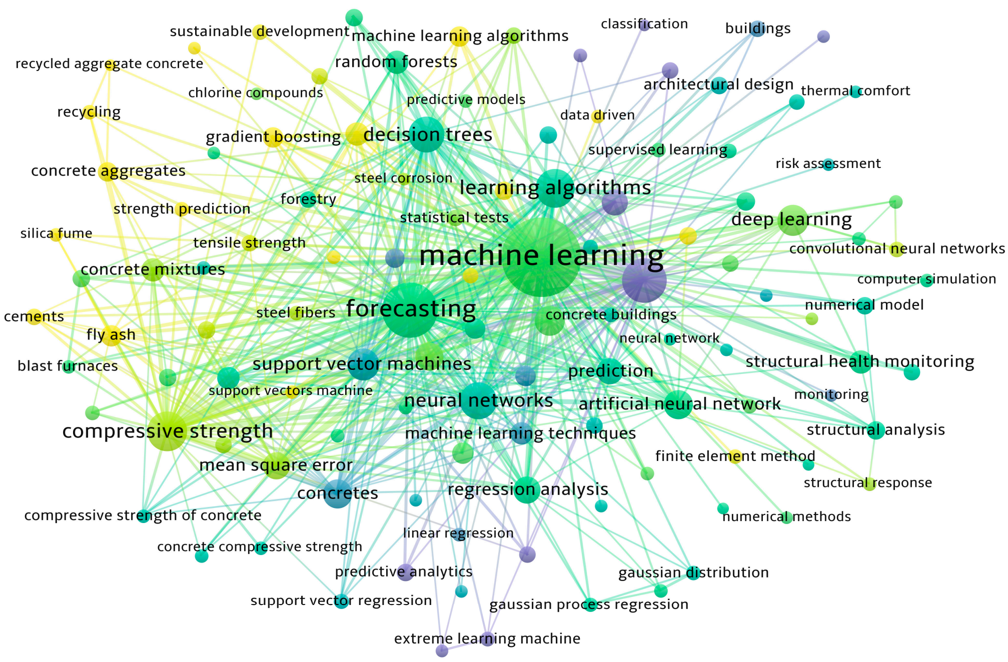

Figure 5. Systematic map of keywords.

3.1.4. Authors and Articles

This section provides an evaluation of influential researchers and literature in the field of ML for pre-earthquake design. Tracking the research activities and highly cited papers of these researchers contributes to understanding the forefront research trends and focal topics in this field. A total of 18 authors have published more than 10 papers in this field. The top three ranked authors are as follows: Khan K. [54], King Faisal University, with 26 papers; Naser M.Z. [55], Clemson University, with 24 papers; and Amin, M.N. [56], King Faisal University, with 24 papers. In this section, the most recent research by the above authors is cited. The sizes of the circles in Figure 6 represent the number of papers published by each author. The larger the number of papers is, the larger the circle is. Additionally, the color intensity of the circles indicates the recency of the papers published by each author. Deeper color indicates more recent publications. The connections between authors in the form of lines represent collaborative relationships. Thicker lines indicate that the two authors connected by the line have appeared more frequently in the same paper collaborations.

Table 4. List of the 20 most commonly used keywords.

S/N	Keywords	Occurrences
1	Machine learning	2241
2	Forecasting	788
3	Learning systems	520
4	Compressive strength	421
5	Learning algorithms	391
6	Neural networks	361
7	Concrete	359
8	Decision trees	350
9	Support vector machines	265
10	Deep learning	253
11	Reinforced concrete	247
12	Artificial neural network	225
13	Machine learning models	218
14	Regression analysis	202
15	Mean square error	200
16	Prediction	186
17	Artificial intelligence	177
18	Concrete mixtures	149
19	Adaptive boosting	148
20	Structural health monitoring	145

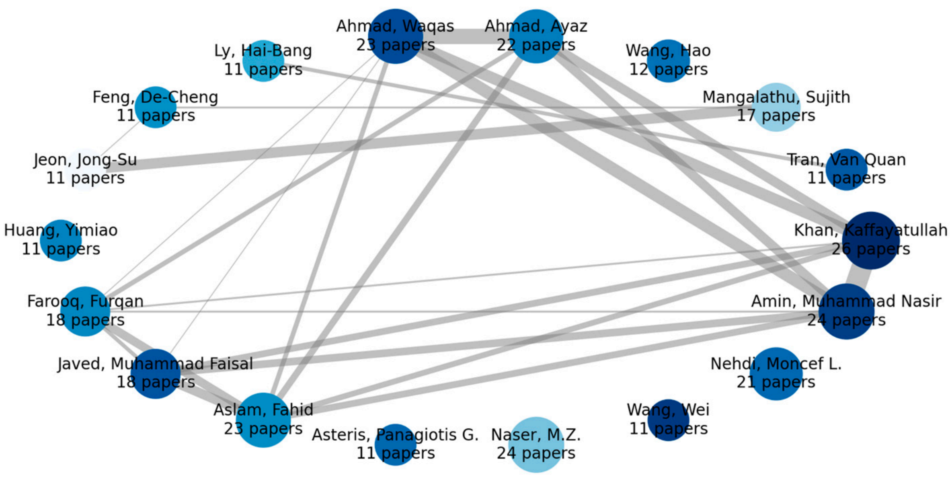

Figure 6. Systematic map of authors.

Tables 5 and 6 present the top 10 most cited papers in the application field of ML in pre-earthquake design [57–66]. From Table 5, it is evident that research related to concrete strength prediction not only exhibits the highest quantity but also commands the greatest citation count, thus signifying its significant prominence as a popular subject. Moving on to Table 6, in comparison to the materials field, the top 5 ML papers with the highest citation frequency in the field of structures and components encompass a broader range of subject fields. One of the prominently favored fields is structural health monitoring. Among the five papers listed in Table 5, four of them, except for one review article, primarily focus on the prediction of compressive strength of concrete. In Feng's [57] study, an adaptive boosting algorithm was employed to predict the compressive strength of concrete. Input data encompassed components of concrete mixtures (such as coarse/fine aggregates, cement, water, additives, etc.) and curing time, while the output data comprised compressive strength values. In Chou's [59] study, even though the subject of research was high-performance concrete, the methodology paralleled Feng's investigation. Similar types of input parameters led to conclusions akin to those of Feng, substantiating the advantage of ensemble algorithms in forecasting concrete strength. The research conducted by Han [60] and Asteris [61] further affirms this proposition, underscoring that ensemble learning holds the potential to be the optimal algorithmic approach for the prediction of concrete strength.

Table 5. The 5 most cited articles in the field of ML for material performance prediction up to 2023.

S/N	Article	Title	Source	Citations
1	Feng D. [57]	Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach	*Construction and Building Materials*	268
2	Ben Chaabene W. [58]	Machine learning prediction of mechanical properties of concrete: Critical review	*Construction and Building Materials*	246
3	Chou J. [59]	Machine learning in concrete strength simulations: Multi-nation data analytics	*Construction and Building Materials*	237
4	Han Q. [60]	A generalized method to predict the compressive strength of high-performance concrete by improved random forest algorithm	*Construction and Building Materials*	172
5	Asteris P. [61]	Predicting concrete compressive strength using hybrid ensembling of surrogate machine learning models	*Cement and Concrete Research*	164

Table 6. The 5 most cited articles in the field of ML for structure and component performance evaluation up to 2023.

S/N	Article	Title	Source	Citations
1	Salehi H. [62]	Emerging artificial intelligence methods in structural engineering	*Engineering Structures*	444
2	Rafiei M. [63]	A novel unsupervised deep learning model for global and local health condition assessment of structures	*Engineering Structures*	262
3	Mangalathu S. [64]	Failure mode and effects analysis of RC members based on machine-learning-based SHapley Additive exPlanations (SHAP) approach	*Engineering Structures*	211
4	Kang D. [65]	Autonomous UAVs for Structural Health Monitoring Using Deep Learning and an Ultrasonic Beacon System with Geo-Tagging	*Computer-Aided Civil and Infrastructure Engineering*	211
5	Tixier A. [66]	Application of machine learning to construction injury prediction	*Automation in Construction*	195

When restricting the publication timeframe to the years 2022–2023, the three most cited papers were authored by Sharati M. [67], Ahmad A. [68], and Kaveh A. [69], with citation counts of 160, 95, and 87, respectively. Sharati M. et al. [67] introduced a novel hybrid ELM-GWO (Extreme Learning Machine-Grey Wolf Optimizer) model by amalgamating the Extreme Learning Machine approach with a metaheuristic algorithm known as Grey Wolf Optimizer. Their work focuses on predicting the compressive strength of partially replaced concrete. Ahmad A. et al. [68] employed supervised ML algorithms including decision trees, bagging regressors, and adaboost regressors to estimate the compressive strength of fly ash-based polymer concrete. Kaveh A. et al. [69] integrated particle swarm optimization, genetic algorithm, colliding bodies optimization, and enhanced colliding bodies optimization algorithms with artificial neural networks to forecast the strength of Fiber-Reinforced Polymers (FRPs). Notably, the investigated materials in these three studies are non-conventional concrete materials, and in contrast to some conventional ensemble learning approaches, these investigations incorporated relatively novel algorithmic methodologies. This underscores the current research focus and trend of utilizing contemporary ML algorithms to assess the mechanical properties of novel materials.

At the structural level, the application of ML techniques has long been proposed. As early as 1991, Moselhi et al. [70] discussed the potential application of neural networks in building engineering. In 1997, Skibniewski et al. [71] applied the AQ15 algorithm on a collection of 31 training examples to automatically learn the mapping between constructability (poor, good, and excellent) and 7 predictors, such as the reinforcement ratio of the beam. In the earlier phases of research, tasks related to structural health monitoring were often conducted based on existing damage reports, which typically offered limited information. In 2010, M. Hakan Arslan [72] conducted numerical modeling of 256 RC buildings with different design parameters, examining their seismic performance. Finally, artificial neural networks were used to predict the seismic performance of the structures, achieving satisfactory results. This study represents an initial exploration of machine learning-based structural earthquake response prediction at the structural level and has garnered a high number of citations. Consequently, in these initial studies, there was a tendency to rely on traditional ensemble algorithms to predict the health status or responses of structures. However, over the past decade, with the widespread adoption of deep learning technologies, structural health monitoring based on more complex image or environmental data has become feasible and has progressively emerged as a research focus. In the two papers in Table 6 related to structural health monitoring, both employed deep learning algorithms. Rafiei et al. [63] proposed a method for assessing the overall and local health status of structural systems using vibration responses collected from sensors. This approach combined synchronous wavelet compression, fast Fourier transformation, and unsupervised deep Boltzmann machines to extract frequency-field features from recorded signals, utilizing probability density functions to establish a Structural Health Index (SHI). Kang et al. [65] introduced a deep convolutional neural network (CNN) method for structural health monitoring using ultrasonic beacons instead of GPS. Both of these studies are grounded in deep learning algorithms, indicating that deep learning is better suited for structural health monitoring tasks involving complex input information than ensemble learning. This might be attributed to the fact that input parameters in structural health monitoring tasks, such as wave or image information, tend to be more intricate than those in concrete strength prediction. Deep learning, particularly convolutional neural networks, exhibits greater proficiency in extracting crucial features from intricate inputs. In addition, many deep learning algorithms in the field of natural language processing demonstrate significant advantages in signal processing. This is because they not only capture the local features of signals but also have the ability to learn the contextual relationships among these local features more extensively.

3.2. Earthquake Prediction

3.2.1. Literature Publication

As depicted in Figure 7, Engineering, Earth and Planetary Sciences, and Computer Science were identified as the top three subject fields within the retrieved literature, accounting for 22.2%, 21.4%, and 16.1% of the total literature, respectively, and contributing to a combined total of 59.7% of the literature. As of 2023, the total number of relevant papers in the field of earthquake prediction reached 599 (Figure 8), which is notably fewer than the volume of literature in the pre-earthquake design field. Earthquake prediction, unlike the forecast of material properties, constitutes a complex, extensive, nascent, and contentious scientific inquiry. Limiting factors such as unclear seismic mechanisms, ambiguous fault structures, incomplete observational data, and uncertain seismic phenomena have impeded its advancement, resulting in limited research outcomes [73–75]. Although debates persist about the feasibility of earthquake prediction, endeavors in earthquake prediction have never ceased. In recent years, an abundance of predictive studies ranging from laboratory-induced seismicity to natural earthquakes have concluded that ML techniques significantly enhance the accuracy of earthquake prediction [76]. Nevertheless, on the whole, the precision of earthquake prediction models remains insufficient, and the volume of related research outcomes remains inadequate.

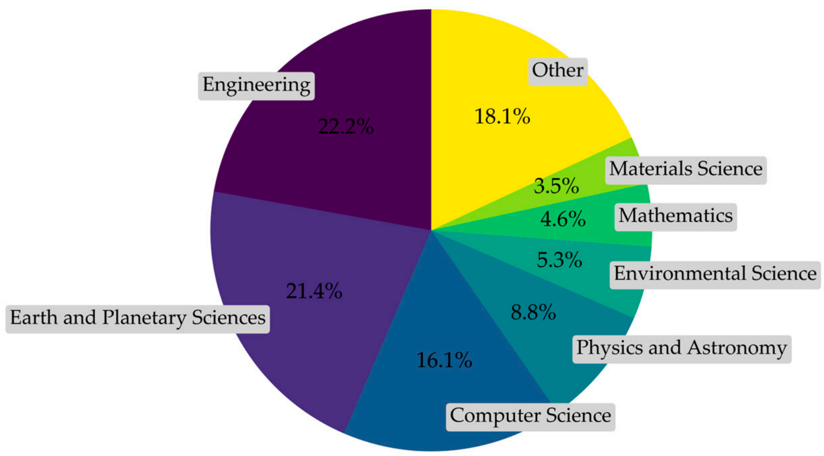

Figure 7. Relevant subject areas for articles from 2011 to 2023.

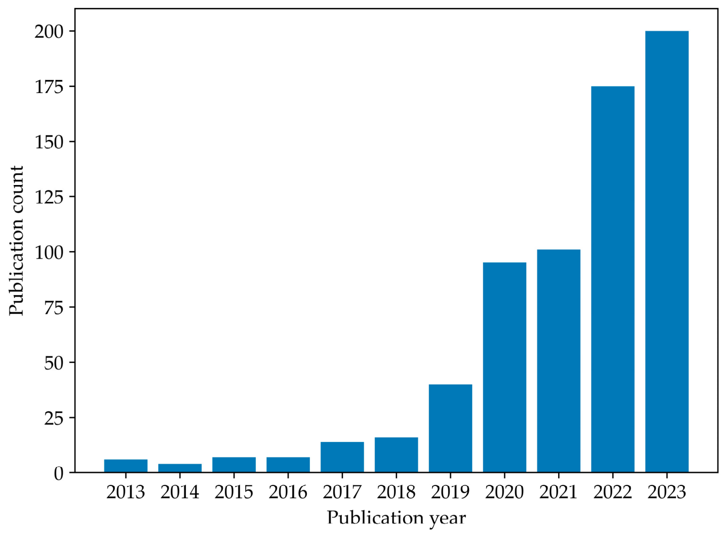

Figure 8. Annual publication trend for articles from 2011 to 2023.

Figure 9 depicts the quantity of literature related to the application of ML in earthquake prediction published by different countries or regions and showcases the collaborative relationships among them. Within Figure 9, the minimum number of papers attributed to a single country or region is constrained to 10, with 21 countries or regions meeting this threshold. The United States, China, and India lead in article counts, contributing 150, 123, and 80 papers, respectively. Furthermore, the United States and China hold the highest citation counts for their papers, with 2564 and 1664 citations, respectively.

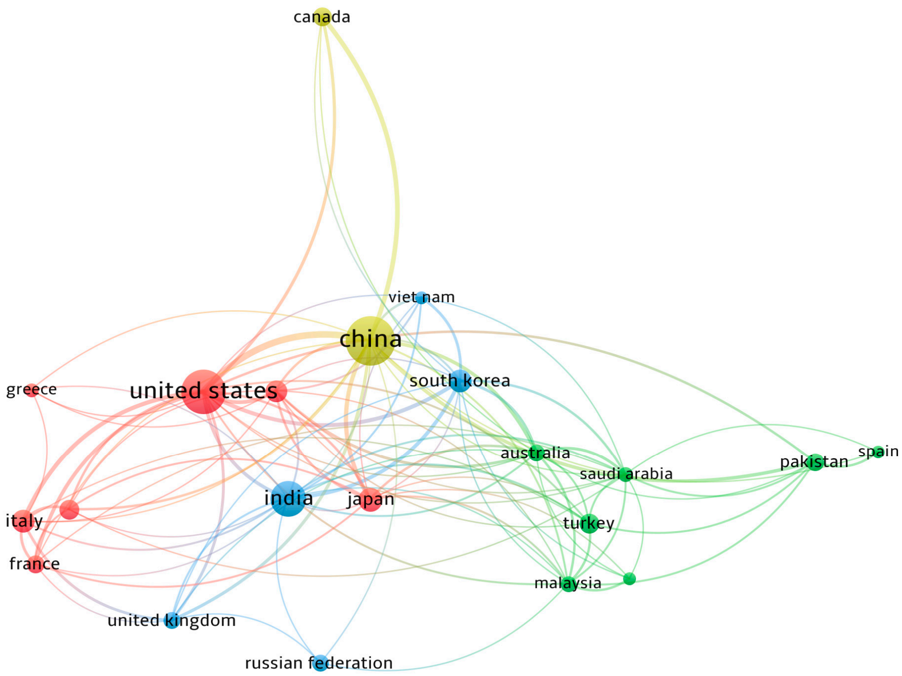

Figure 9. Systematic map of countries that presented a minimum of 10 articles.

3.2.2. Publication Sources

Tables 7 and 8 present the top five publishers with the highest number of publications as of 2023 as well as the top five publishers with the highest citation counts during this period. *Soil Dynamics and Earthquake Engineering*, *Applied Sciences (Switzerland)*, and *Engineering Structures* were the top publication journals with 18, 16, and 16 papers, respectively. In addition, between 2013 and 2023, *Geophysical Research Letters*, *Engineering Structures*, and *Soil Dynamics and Earthquake Engineering* were cited the most, with 434, 390, and 378 citations, respectively.

Table 7. Top 5 most cited journals as of 2023.

S/N	Source Name	Total Publications	Total Citations
1	*Soil Dynamics and Earthquake Engineering*	18	378
2	*Applied Sciences (Switzerland)*	16	139
3	*Engineering Structures*	16	390
4	*Seismological Research Letters*	11	318
5	*Frontiers in Earth Science*	11	29

Figure 10 shows a visualization of a source that has published at least 5 articles, with only 26 published sources meeting the requirements. As can be seen from the figure, *Soil Dynamics and Earthquake Engineering*, *Applied Sciences (Switzerland)*, and *Engineering Structures* are the most influential journals in the field of earthquake prediction.

Table 8. Top 5 most cited journals as of 2023.

S/N	Source Name	Total Publications	Total Citations
1	*Geophysical Research Letters*	7	434
2	*Engineering Structures*	16	390
3	*Soil Dynamics and Earthquake Engineering*	18	378
4	*Seismological Research Letters*	11	318
5	*Natural Hazards*	11	231

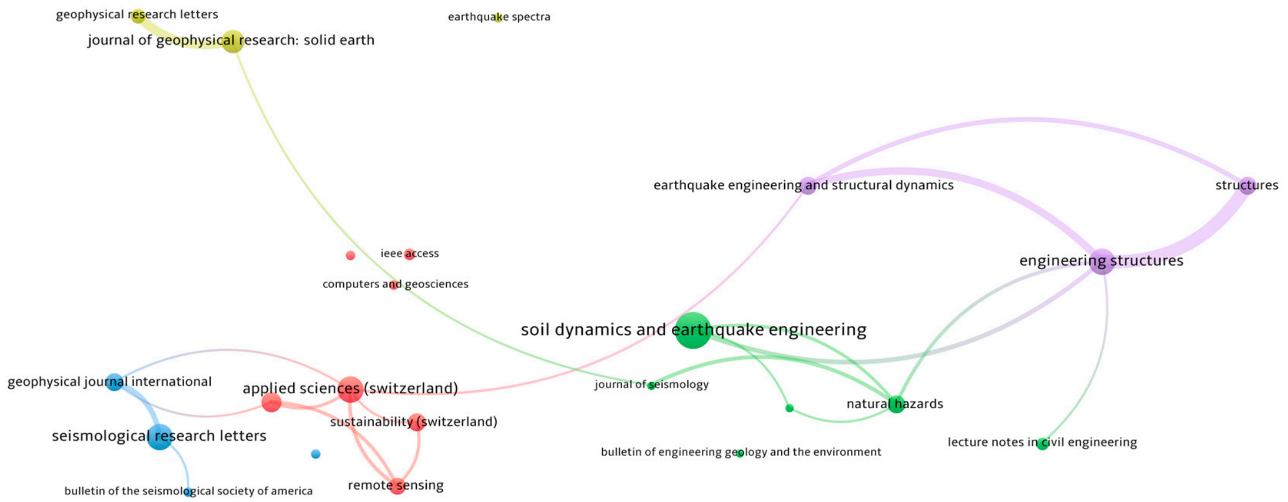

Figure 10. Systematic map of journals that published a minimum of 5 documents.

3.2.3. Keywords

Table 9 records the 20 most commonly used keywords in published articles (appearing at least 20 times). The five terms that come up most frequently in the subject area of research are machine learning, earthquakes, forecasting, learning algorithms, and earthquake prediction. Figure 11 illustrates the keyword co-occurrence and connection-based system map. From Figure 11, it is evident that apart from earthquake and forecasting, various ML algorithms constitute the most frequent keywords. The three most prevalent ML algorithms are deep learning, artificial neural networks, and decision trees. Similar to the pre-earthquake design field, these algorithms represent some of the early classical methodologies, while certain more advanced algorithms introduced in recent years have yet to receive widespread application. Furthermore, as discerned from Table 9, earthquake catalogs emerge as the most prevalent input data source within current ML practices. These catalogs encompass seismic magnitudes, spatial coordinates, and temporal information. Typically, earthquake catalogs undergo preprocessing or transformation leveraging according to prior seismic regularities. Subsequently, these transformed catalogs serve as inputs for ML training, modeling, and prediction. For instance, Alarifi et al. [77] transformed earthquake occurrence times into sequential numbers and converted seismic location attributes (latitude, longitude, and depth) and magnitude into pre-defined grids for training and prediction purposes. Panakka et al. as well as Adeli et al. [78,79] derived eight seismic activity parameters as indicators from the earthquake catalog based on two earlier statistical models, the Gutenberg-Richter power-law relationship (G-R relationship), and the characteristic earthquake model. These activity parameters have even evolved into an extended set of seismic parameters; Asim et al. [80] proposed 60 such parameters, although some studies have employed only a subset of these parameters [81].

Table 9. List of the 20 most commonly used keywords.

S/N	Keywords	Occurrences
1	machine learning	504
2	earthquakes	355
3	forecasting	241
4	learning algorithms	151
5	earthquake prediction	123
6	earthquake catalog	123
7	prediction	94
8	deep learning	76
9	artificial neural network	74
10	decision trees	74
11	neural networks	71
12	support vector machines	64
13	earthquake engineering	56
14	earthquake event	56
15	seismic response	54
16	seismology	53
17	earthquake magnitude	51
18	damage detection	46
19	regression analysis	45
20	ground motion	44

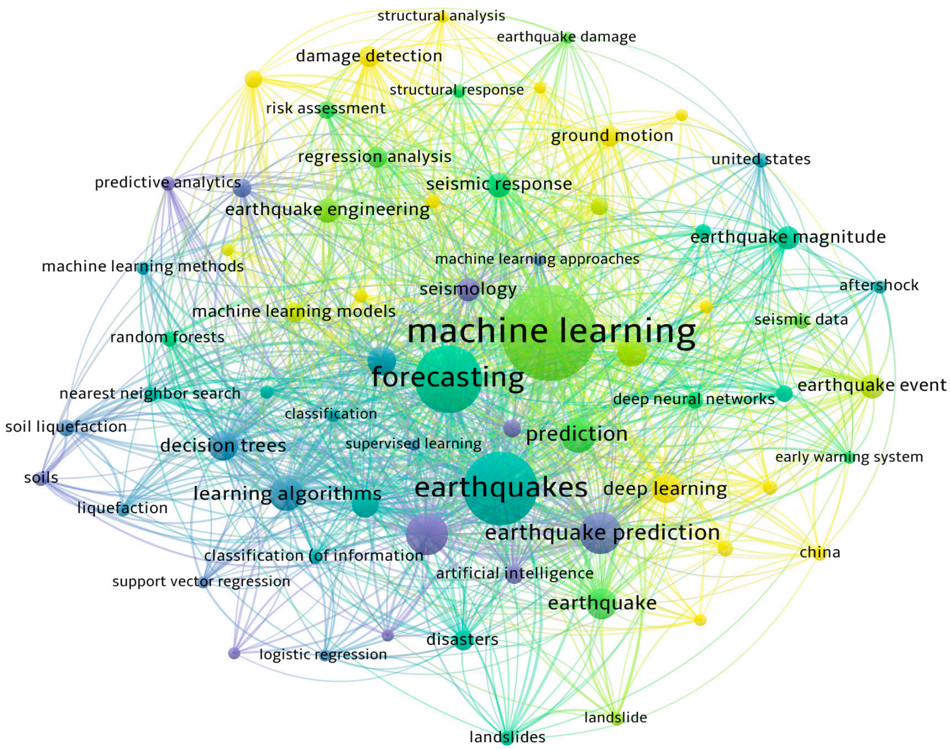

Figure 11. Systematic map of keywords.

Furthermore, keywords such as rock instability, electromagnetic phenomena, and subsurface fluids exhibit a remarkably low frequency of occurrence, even though some scholars contend that these factors could potentially enhance the precision of earthquake prediction. Certain researchers posit that the current limitations in the predictive capabilities of ML models for earthquakes might be linked to the one-sided and monotonous nature of data inputs. For instance, Hulbert et al. [82] suggest that by employing more primal and foundational observations of rock instability or fracture data, ML could likely discern a broader spectrum of precursor features, thereby augmenting the accuracy of earthquake prediction. This perspective finds partial validation in the research of several scholars. For instance, Rouet-Leduc et al. [83], utilizing continuously recorded seismic waveform data, significantly improved predictions regarding rock instability and successfully captured features of subduction zone fault activity, thereby contributing to accurate earthquake forecasts. Moreover, there exists a plethora of natural features and a wealth of field observation data (spanning various disciplines such as surface deformation, gravity, geochemistry, and other multidisciplinary data) that remain underutilized in earthquake prediction research. Faqueeh et al. [84] highlight that the enhanced accuracy of ML models for earthquake prediction can be further achieved through interdisciplinary collaboration or concerted involvement of researchers, thereby harnessing the potential of diverse disciplines to advance the capabilities of these models.

3.2.4. Authors and Documents

A total of 8 authors have published more than 4 papers in this field (Figure 12). The top three ranked authors are as follows: Zhang, Miao [85], Dalhousie University, with 7 papers; Martínez-Álvarez, F. [86], Pablo de Olavide University of Seville, with 6 papers; Samui, P. [87], NIT Patna, with 6 papers. In this section, the most recent research by the above authors is cited.

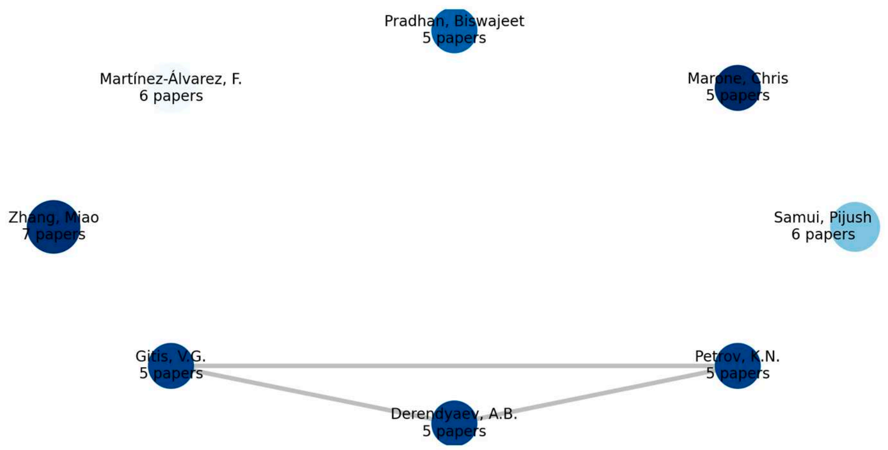

Figure 12. Systematic map of authors.

Tables 10 and 11 list the 10 most cited papers in the field of ML in earthquake prediction. As can be seen from Tables 10 and 11, influential papers tend to use ML techniques to predict earthquakes occurring in specific countries or regions. Reyes J. [88] used artificial neural networks to make predictions about possible earthquakes in Chile. The input values are related to the b-value, the Bath's law, and the Omori-Utsu's law, parameters that are strongly correlated with seismicity. Asim K.M. [89] used time series of historical seismic activity combined with ML classifiers to predict earthquake magnitudes in the Hindukush region. Rafiei M.H. [90] has proposed a new Earthquake Early Warning System (EEWS) model based on seismic activity indicators, called Neural EEWS (NEEWS), based on earthquake data from Southern California. The model utilizes a combination of a classification algorithm based on ML concepts and a mathematical optimization algorithm to predict the magnitude and location of earthquakes weeks before they occur. In Karimzadeh's study [91], records of aftershocks (with a magnitude greater than 2.5) from the first second after the occurrence of the Iran Kermanshah earthquake (with a magnitude of 7.3 on the Richter scale) until the end of September 2018 were collected. Various ML algorithms, including Naive Bayes, k-nearest neighbors, support vector machines, and random forests, were used to predict the aftershock patterns. These predictions were based on factors such as a sliding distribution, changes in Coulomb stress on the fault plane (inferred from synthetic aperture radar images), and the direction of neighboring active faults.

Papers [92–94] all address the analysis and processing of earthquake data, particularly focusing on utilizing ML and deep learning methods to enhance the processing and interpretation of earthquake data. Zhu [92] introduced a convolutional neural network-based phase identification classifier for phase detection and picking of earthquake data with limited labeled events. This approach achieves high accuracy and improved earthquake arrival time prediction even with a reduced training set size. Liu [93] analyzed continuous earthquake data from the July 2019 Ridgecrest earthquake sequence in California using deep neural network techniques. This study achieved automatic earthquake detection and localization, revealing the spatiotemporal evolution of the earthquake sequence and identifying multiple activated faults within the sequence. The research demonstrates that well-trained ML methods and workflows can extract seismic sequence characteristics from raw earthquake data. Mignan [94] focuses on seismic bursts in Southern California, identifying clusters of small earthquakes with observable properties, such as a radius of gyration (RG), that connect to the occurrence of large earthquakes, displaying cycles of dynamics related to stress accumulation and release, suggesting improved earthquake nowcasting potential.

Table 10. The 5 most cited articles in the field of ML for mainshock prediction up to 2023.

S/N	Article	Title	Source	Citations
1	Kong Q. [95]	Machine learning in seismology: Turning data into insights	*Seismological Research Letters*	265
2	Rouet-Leduc B. [96]	Machine Learning Predicts Laboratory Earthquakes	*Geophysical Research Letters*	222
3	Reyes J. [88]	Neural networks to predict earthquakes in Chile	*Applied Soft Computing Journal*	138
4	Asim K.M. [89]	Earthquake magnitude prediction in Hindukush region using machine learning techniques	*Natural Hazards*	119
5	Rafiei M.H. [90]	NEEWS: A novel earthquake early warning model using neural dynamic classification and neural dynamic optimization	*Soil Dynamics and Earthquake Engineering*	110

Table 11. The 5 most cited articles in the field of ML for aftershock prediction up to 2023.

S/N	Article	Title	Source	Citations
1	Zhu L. [92]	Deep learning for seismic phase detection and picking in the aftershock zone of 2008 Mw7.9 Wenchuan Earthquake	*Physics of the Earth and Planetary Interiors*	77
2	Liu M. [93]	Rapid Characterization of the July 2019 Ridgecrest, California, Earthquake Sequence From Raw Seismic Data Using Machine-Learning Phase Picker	*Geophysical Research Letters*	61
3	Mignan A. [94]	Neural network applications in earthquake prediction (1994–2019): Meta-analytic and statistical insights on their limitations	*Seismological Research Letters*	51

Table 11. *Cont.*

S/N	Article	Title	Source	Citations
4	Rundle J.B. [97]	Nowcasting Earthquakes in Southern California With Machine Learning: Bursts, Swarms, and Aftershocks May Be Related to Levels of Regional Tectonic Stress	*Earth and Space Science*	18
5	Karimzadeh S. [91]	Spatial prediction of aftershocks triggered by a major earthquake: A binary machine learning perspective	*ISPRS International Journal of Geo-Information*	16

3.3. Post-Earthquake Assessment

3.3.1. Literature Publication

As depicted in Figure 13, Engineering, Earth and Planetary Sciences, and Materials Science were identified as the top three subject fields within the retrieved literature, accounting for 58.8%, 25.3%, and 6.2% of the total literature, respectively, and contributing to a combined total of 90.3% of the literature. As of 2023, the total number of relevant papers in the field of post-earthquake assessment reached 56 (Figure 14). It is evident that when the research focus shifts to post-earthquake structures, the application of ML techniques in the fields of structural damage and residual performance assessment remains relatively limited, despite its extensive use in pre-earthquake construction scenarios, such as material or structural surface defect detection and structural performance evaluation. In the field of damage assessment, compared to pre-earthquake structures, the damage phenomena observed on post-earthquake damaged structures are more severe and intricate. The existing post-earthquake damaged structural databases suitable for deep learning are still insufficient [98], thereby constraining the progress of relevant research. In the field of residual performance assessment for post-earthquake damaged structures, researchers similarly encounter a deficiency of reliable training data to effectively train ML models. Despite the existence of certain numerical simulation methodologies, such as post-earthquake damaged structural numerical simulations based on aftershock sequences [99–103], some scholars argue that the responses obtained from such approaches may diverge from the actual post-earthquake responses of damaged structures [104]. Consequently, some scholars attempt to establish numerical models directly from the damaged states to simulate their post-earthquake responses and build datasets for training ML models to predict their post-earthquake behaviors [105–107]. In conclusion, employing ML techniques for damage and residual performance assessment of post-earthquake damaged structures represents a promising avenue for research. This endeavor holds the potential to enhance the existing assessment procedures, which often overly rely on the expertise of evaluators and exhibit limitations in terms of efficiency.

Figure 15 depicts the quantity of literature related to the application of ML in post-earthquake assessment published by different countries or regions and showcases the collaborative relationships among them. Within Figure 15, the minimum number of papers attributed to a single country or region is constrained to 3, with 10 countries or regions meeting this threshold. Among them, only the United States and China have more than 10 papers, with 20 papers and 16 papers, respectively, garnering citation counts of 643 and 149, respectively. In contrast, Canada, despite possessing only 5 papers, has accumulated a total of 200 citations.

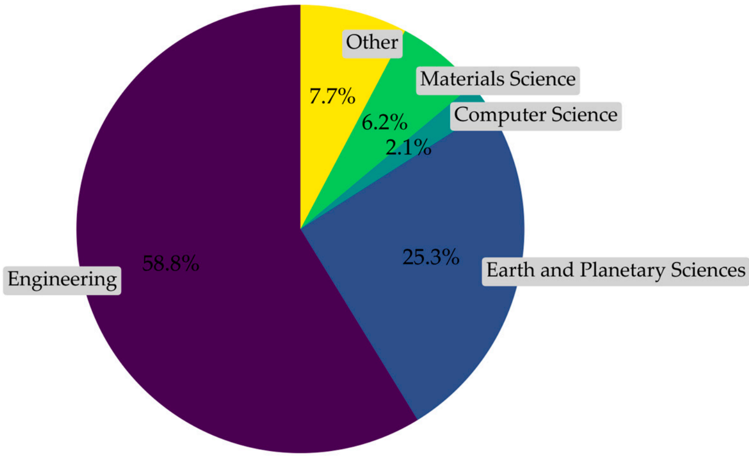

Figure 13. Relevant subject areas for articles from 2018 to 2023.

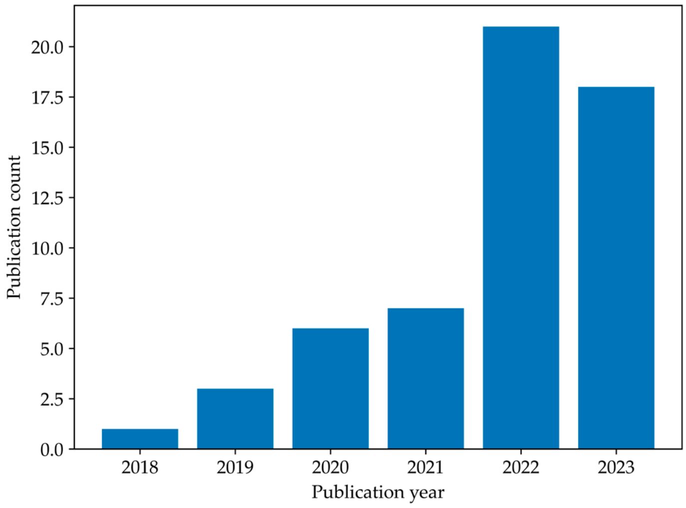

Figure 14. Annual publication trend for articles from 2018 to 2023.

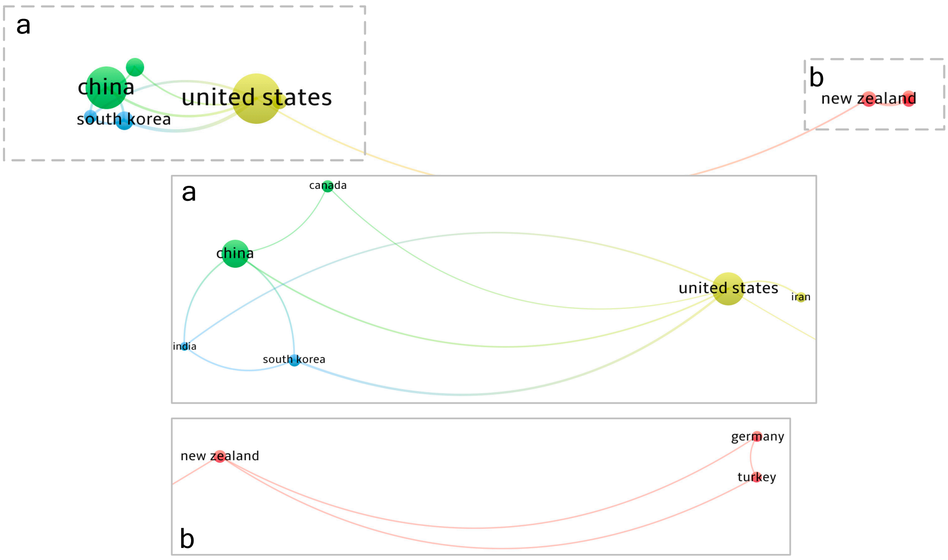

Figure 15. Systematic map of countries that presented a minimum of 3 articles (Subfigures (**a**,**b**) represent magnified views of Figure 15).

3.3.2. Publication Sources

Tables 12 and 13 present the top five publishers with the highest number of publications as of 2023 as well as the top five publishers with the highest citation counts during this period. *Engineering Structures*, *Earthquake Spectra*, and *Structures* were the top publication journals with 12, 8, and 6 papers, respectively. In addition, between 2013 and 2023, *Earthquake Spectra*, *Engineering Structures*, and *Structural Health Monitoring* were cited the most, with 360, 194, and 162 citations, respectively.

Table 12. Top 5 most cited journals as of 2023.

S/N	Source Name	Total Publications	Total Citations
1	*Engineering Structures*	12	194
2	*Earthquake Spectra*	8	360
3	*Structures*	6	49
4	*Earthquake Engineering and Structural Dynamics*	6	96
5	*Bulletin of Earthquake Engineering*	5	14

Table 13. Top 5 most cited journals as of 2023.

S/N	Source Name	Total Publications	Total Citations
1	*Earthquake Spectra*	7	360
2	*Engineering Structures*	16	194
3	*Structural Health Monitoring*	18	162
4	*Earthquake Engineering and Structural Dynamics*	11	96
5	*Journal of Building Engineering*	11	54

Figure 16 shows a visualization of a source that has published at least 3 articles, with only 8 published sources meeting the requirements. As can be seen from the figure, *Engineering Structures*, *Earthquake Spectra*, and *Earthquake Engineering and Structural Dynamics* are the most influential journals in the field of earthquake prediction.

3.3.3. Keywords

Table 14 records the 20 most commonly used keywords in published articles (appearing at least 6 times). The five terms that come up most frequently in the subject area of research are machine learning, damage detection, earthquake damage, earthquakes, and learning systems. Figure 17 illustrates the keyword co-occurrence and connection-based system map. Based on Table 14 and Figure 17, it can be observed that ML is primarily employed for damage detection in post-earthquake damaged structures, predominantly in reinforced concrete structures. The most commonly utilized algorithm is deep learning. Subsequent applications include damage state classification and risk assessment in post-earthquake damaged structures, with decision trees being the prevailing algorithm in this field. Furthermore, "learning systems" is also frequently mentioned, indicating that researchers are actively promoting the practical application of machine learning techniques in post-earthquake assessments.

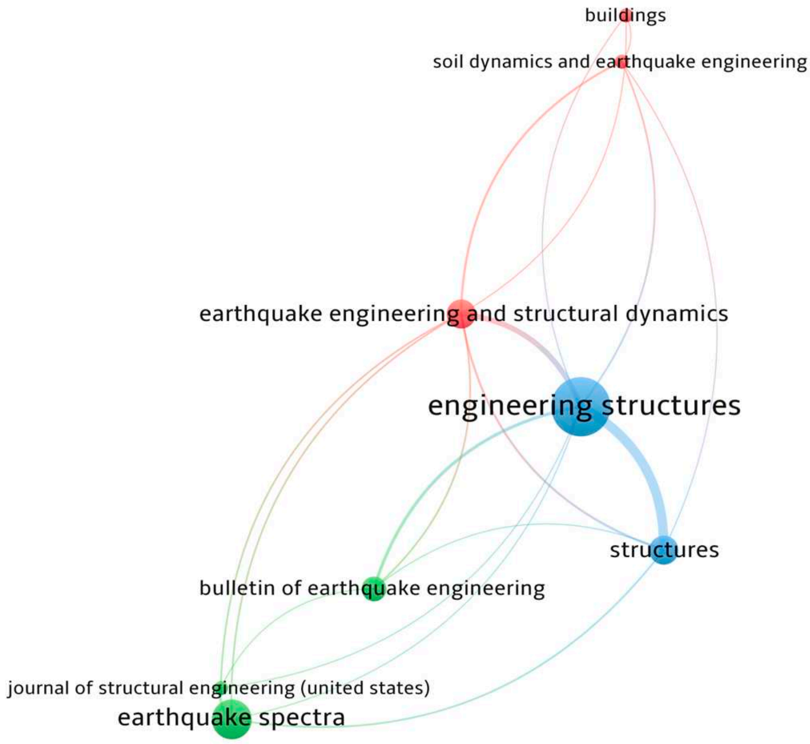

Figure 16. Systematic map of journals that published a minimum of 3 documents.

Table 14. List of the 20 most commonly used keywords.

S/N	Keywords	Occurrences
1	machine learning	56
2	damage detection	37
3	earthquake damage	37
4	earthquakes	24
5	learning systems	19
6	reinforced concrete	14
7	seismic response	14
8	seismology	13
9	building	12
10	deep learning	12
11	decision trees	12
12	earthquake engineering	12
13	forecasting	12
14	damage state	11
15	structural analysis	10
16	learning algorithms	9
17	risk assessment	9
18	structural health monitoring	9
19	artificial neural network	7
20	ground motion	7

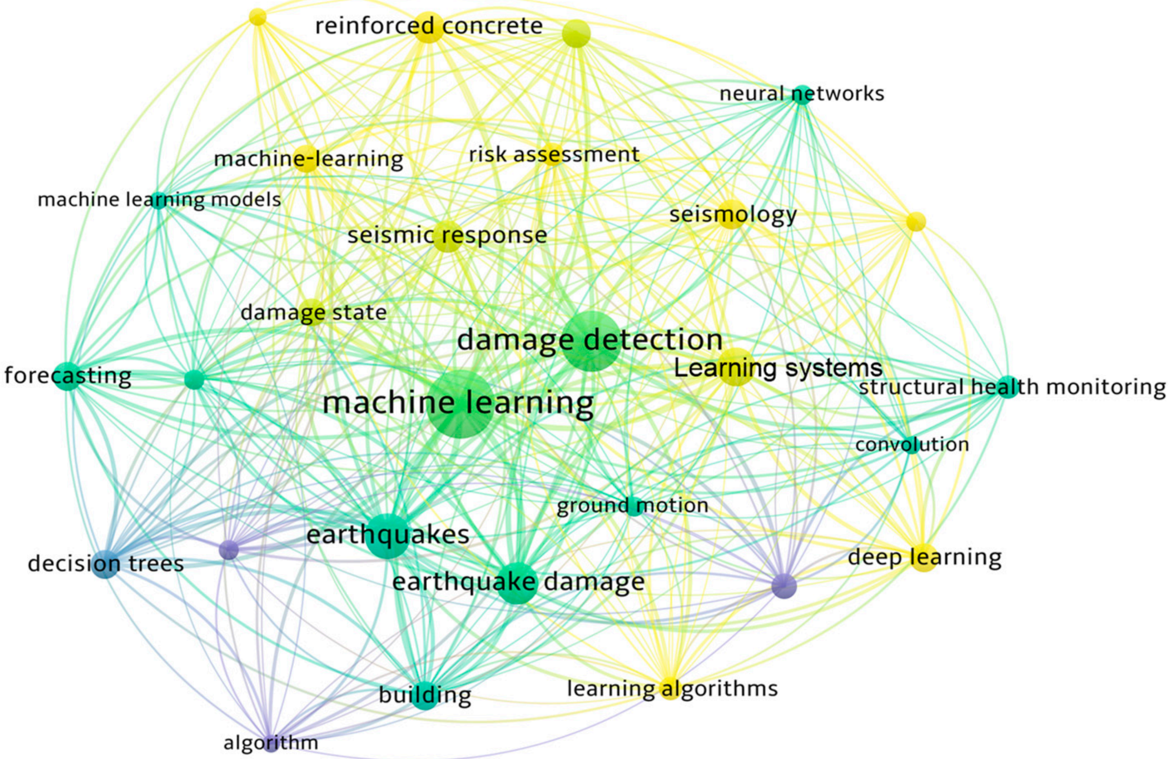

Figure 17. Systematic map of keywords.

3.3.4. Authors and Documents

A total of 19 authors have published more than 1 paper in this field (Figure 18). The top two ranked authors are as follows: Liang, Xiao [13], The State University of New York, with 3 papers; Jeon, Jong-Su [108], Hanyang University, with 3 papers. Tables 15 and 16 list the 10 most cited papers in the field of ML in post-earthquake assessment.

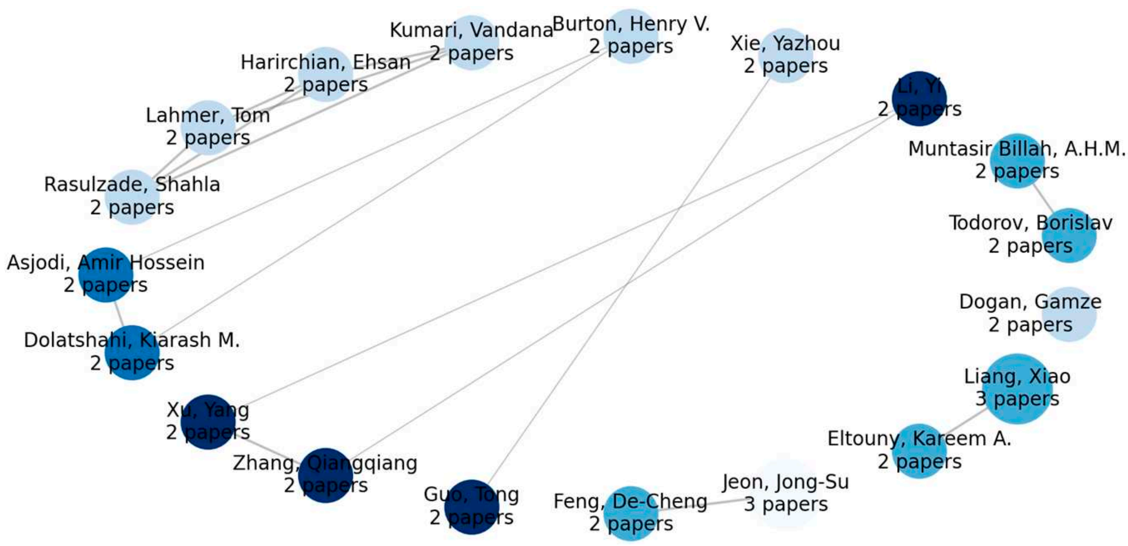

Figure 18. Systematic map of authors.

Table 15. The 5 most cited articles in the field of ML for damage identification up to 2023.

S/N	Article	Title	Source	Citations
1	Xie Y. [109]	The promise of implementing machine learning in earthquake engineering: A state-of-the-art review	*Earthquake Spectra*	173
2	Yu Y. [110]	A novel deep learning-based method for damage identification of smart building structures	*Structural Health Monitoring*	162
3	Harirchian E. [111]	A review on application of soft computing techniques for the rapid visual safety evaluation and damage classification of existing buildings	*Journal of Building Engineering*	52
4	Gao Y. [112]	PEER Hub ImageNet: A Large-Scale Multiattribute Benchmark Data Set of Structural Images	*Journal of Structural Engineering (United States)*	37
5	Eltouny K.A. [113]	Bayesian-optimized unsupervised learning approach for structural damage detection	*Computer-Aided Civil and Infrastructure Engineering*	29

Table 16. The 5 most cited articles in the field of ML for residual performance evaluation up to 2023.

S/N	Article	Title	Source	Citations
1	Mangalathu S. [29]	Classifying earthquake damage to buildings using machine learning	*Earthquake Spectra*	113
2	Mangalathu S. [27]	Rapid seismic damage evaluation of bridge portfolios using machine learning techniques	*Engineering Structures*	96
3	Lu X. [114]	A deep learning approach to rapid regional post-event seismic damage assessment using time-frequency distributions of ground motions	*Earthquake Engineering and Structural Dynamics*	53
4	Roeslin S. [115]	A machine learning damage prediction model for the 2017 Puebla-Morelos, Mexico, earthquake	*Earthquake Spectra*	25
5	Nguyen H.D. [116]	Rapid seismic damage-state assessment of steel moment frames using machine learning	*Engineering Structures*	19

Yu Y. [110] proposed a method for structural damage identification and localization based on deep convolutional neural networks capable of automatically extracting high-level or low-level features from raw signals. This approach, distinct from traditional manual feature extraction methods, significantly enhances the efficiency and practicality of ML models. Gao Y. [112] introduced a comprehensive automated framework, named Pacific Earthquake Engineering Research (PEER) Hub ImageNet (φ-Net), defining eight benchmark classification tasks based on field knowledge and past experiences. These paired images and labels can directly facilitate similar classification tasks, and the original structural images can further be used for target localization and segmentation in future research. Eltouny K.A. [113] proposed a density-based unsupervised learning method for structural damage detection and localization, which, for the first time in unsupervised learning methods, utilizes accumulated intensity measurements to extract damage-sensitive features. In the aforementioned studies related to structural damage identification, the authors collectively emphasized the lack of high-quality datasets suitable for damage identification as a significant constraint in this field, and they each proposed different approaches within their research to address this limitation.

In the post-earthquake residual performance assessment field, Mangalathu S. [27,29] attempted the feasibility of rapidly predicting the damage condition and residual capacity of post-earthquake damaged structures using ML techniques such as discriminant analysis, k-nearest neighbors, decision trees, and random forests, and verified and validated these approaches on both civil buildings and bridges. Lu X. [114] introduced a swift post-event seismic damage assessment technique based on convolutional neural networks (CNNs). The approach amalgamates building inventories, projected ground motion datasets, and corresponding damage levels into a scenario repository. Subsequently, time-frequency distribution graphs of ground motions are created, providing intricate visual depictions of both frequency and time field attributes. These data serve as training inputs for CNN models to forecast damage states. The efficacy of this approach is demonstrated through two numerical assessments: one involving a single building and the other a regional scenario encompassing structures on the Tsinghua University campus. Roeslin S. [115] developed an ML framework to assess the earthquake damage of buildings based on the damage information and structural characteristics of 340 buildings damaged during the 2017 Puebla earthquake in Mexico City. Nguyen H.D. [116] trained ML models using various ML algorithms and post-earthquake damaged steel frame response data obtained through numerical simulations to predict their residual performance. Yilmaz M. and Dogan G. et al. [117] developed an innovative deep learning-based intelligent software (DamageNet) along with its mobile application for classifying seismic damage to RC components.

In the aforementioned studies, supervised ML algorithms were employed, where the residual performance of different post-earthquake damaged structures in the training set was manually assessed and predefined. The training data for these studies originated from data collected during actual seismic events or numerical simulations. However, these research methodologies are similarly constrained by the scarcity of training data; obtaining high-quality usable data from actual seismic events is not straightforward, and training data derived from numerical simulations may suffer from issues of credibility. Considering the uncontrollable nature of earthquakes, the development of more accurate and rational numerical models for post-earthquake damaged structures to obtain credible post-earthquake response data is a highly promising research field. This would contribute to generating more usable datasets for ML training.

Apart from the applications discussed in the preceding sections, ML technology actually holds many potential applications in earthquake engineering. For instance, in post-earthquake assessment, some damaged buildings need to be demolished while others can be reinforced and continue to be used. ML technology can provide strong support for both the debris clearing of demolished buildings and the strengthening work on buildings still in use.

Earthquakes can cause varying degrees of destruction, resulting in a large amount of debris. For example, in the Great East Japan Earthquake, Iwate, Miyagi, and Fukushima Prefectures alone had one million tons of building debris [118]. Managing such a huge amount of debris requires special attention. Therefore, it is crucial to develop a comprehensive and cost-effective management plan. According to the authors' current investigation, ML technology, particularly computer vision technology, has been applied to some extent in the post-earthquake debris recovery work. For example, Trotta O et al. [119] developed a method based on short-wave infrared (1000–2500 nm) hyperspectral imaging and applied it to characterize the recycling of post-earthquake building debris. Bonifazi G et al. [120] studied a method based on automatic sensors to identify and classify different post-disaster buildings and building debris for recycling as secondary raw materials. However, there is still very little research on resource calculation related to the recovery of this debris. Exploring how to utilize ML technology for more rational management of building debris is a promising area of research.

In the field of post-earthquake strengthening, many studies have already provided models to assess whether damaged buildings are suitable for continued use after strengthening and have offered some simple recommendations. However, the focus of these studies is on evaluating the residual performance of damaged buildings to determine their suitability for continued use after strengthening, rather than using ML methods to develop specific strengthening strategies. Once the strengthening methods have been determined, there are many methods available to predict the performance of the buildings after strengthening [121–123]. These studies have employed various ML methods to predict the post-strengthening performance of structures or components strengthened with materials such as FRP and UHPC. The authors believe that using ML methods to specify the most appropriate strengthening scheme rather than simply predicting the performance of buildings that have already been strengthened may be a potential research direction.

4. Conclusions

The purpose of this study was to conduct a scientometric evaluation of the specific applications of ML in earthquake engineering based on existing literature. To achieve this objective, a scientometric analysis was performed on 3189 papers from the Scopus database using VOSviewer, leading to the following conclusions:

(1) Among the 3189 papers analyzed, the majority of research outcomes were in the field of seismic design (including material performance and the assessment of structural and component performance), totaling 2534 papers. The second most prolific field was earthquake prediction (encompassing both mainshock and aftershock prediction) with 599 papers, while the field of post-earthquake assessment (including damage identification and post-earthquake residual performance evaluation) had the fewest research outcomes, comprising only 56 papers.

(2) China and the United States emerged as the top two major source countries for these papers. In the field of seismic design, the publisher with the highest number of publications was *Construction and Building Materials*, while the publisher with the most citations was also *Construction and Building Materials*. In the field of earthquake prediction, the publisher with the highest number of publications was *Soil Dynamics and Earthquake Engineering*, and the one with the most citations was *Geophysical Research Letters*. In the field of post-earthquake assessment, the publisher with the most publications was *Engineering Structures*, and the most cited publisher was *Earthquake Spectra*.

(3) In the pre-earthquake design field, the application of ML was predominantly focused on predicting material performance, particularly concrete compressive strength prediction using ensemble algorithms. In the field of earthquake prediction, current research is concentrated on predicting earthquakes in specific regions based on earthquake catalogs and collecting and processing earthquake signals. In the post-earthquake assessment field, current research mainly revolves around using deep learning algorithms from ML to identify damage information in earthquake-damaged structures and to replace manual grading and classification of structural damage states.

(4) By discussing the viewpoints and prospects presented in the most cited papers in each field, it is possible to identify shortcomings in existing research and future trends. In the seismic design field, ML has demonstrated excellent performance in predicting material properties, and future research trends involve evaluating the performance of concrete with new materials using novel algorithms. In the field of earthquake prediction, existing research indicates that making full use of rich field

observation data (such as various multidisciplinary data like surface deformation, gravity, electromagnetic, subsurface fluid, and geochemical data) may enhance the accuracy of earthquake prediction and is a current developmental trend. In the post-earthquake assessment field, existing research highlights the lack of accessible high-quality databases as a major hindrance to the progress of damage identification and residual performance assessment of earthquake-damaged structures. One of the future trends is to obtain reliable and reasonable databases through experimental or numerical simulation methods for training ML models.

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