International Journal of Engineering, Science and Mathematics
Vol. 8 Issue 6, June 2019, ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: ijesmj@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

Machine learning aids earthquake risk prediction: Empirical Study

Yeruva Ramana Reddy

Software Engineer & Department of Civil Engineering

Indian Institute of Technology, India

yramanareddyiit@gmail.com

Abstract—*The main purpose of this research is to examine how earthquake risk prediction might be improved by using machine learning. Seismological machine learning has experienced a dramatic increase in the last five years. Workflows for monitoring earthquakes include detection, measuring arrival time, associating phases, determining location, and characterizing [1]. Machine-learning techniques have made remarkable progress on all of these tasks. Big, labelled data sets, typically publicly accessible and built up over decades of committed labour by trained analysts, have made them ideal targets for learning algorithms in seismic interpretation. Complex supervised models need this component. Researchers have made significant progress in analysing the intricacies of earthquakes long after the quakes have happened, and machine-learning algorithms are ready to be used in operational mode. In the near future, we'll have new earthquake catalogs with a lot more information [1]. More comprehensive catalogs often include at least a tenfold increase in the number of earthquakes and give a more detailed picture of active faults.*

Keywords: Machine learning, earthquake risk prediction, seismic hazard analysis, civil engineering, structural control, seismic fragility assessment

I. INTRODUCTION

Natural disasters like earthquakes occur when the earth's tectonic plates shift or are displaced. As a result of the enormous quantity of energy released during this sudden displacement, seismic waves are generated. Those who reside in earthquake impact zones were harmed by the earthquake's resulting vibrations. Indonesia, a nation with a population of more than 300 million people, is situated in the world's most quake-prone zone since it is home to around 127 active volcanoes [1]. This region is often known as the Ring of Fire because it is home to the most intense tectonic action. Furthermore, Indonesia possesses the Great Sumatran Fault, which spans 1900 kilometres, and the Banda Sea convergent flat edge, which causes even greater seismic activity.

There is a long and contentious history of earthquake risk prediction, which necessitates figuring out when, where, and how big the event will happen in advance. It's taken a lot of work to get this far, and although there have been some encouraging signs along the way, the overall results have been disappointing. As a consequence, many have concluded that short-term earthquake prediction is difficult at best. Earthquakes can only be predicted by "fools, charlatans, and liars," in the words of Charles Richter himself.

The earthquake research community now has access to a new set of methods that can be applied to this age-old subject courtesy to machine learning (ML). Nevertheless, bringing ML to the forecasting model creates several challenging concerns, such as how to appropriately assess outcomes on uncommon occurrences, what to do about modelling techniques that appear to have significant predictive ability but may not general, and how to manage the outputs of ambiguous ML techniques. These are just a few examples of the challenges that arise when using ML to the prediction problem. Progress has been made on certain elements of the prediction issue despite these difficulties. For instance, machine learning has shown that certain kinds of tectonic earthquakes, also referred as slow slip incidents, may be predicted based on statistical features retrieved from seismic surveys [1,2]. This is true for both the amount of time that is left until an earthquake strikes in the research lab and for slow slip incidents. The subject of predicting earthquakes in a laboratory is summarized in the section that follows.

II. RESEARCH PROBLEM

The main problem that will be solved by this paper is to analyze how machine learning may be used to forecast earthquake risk. Earthquakes and other natural disasters, such as soil liquefaction, landslides, tsunamis, floods, and fires, pose a threat to highways. Concerns regarding the seismic vulnerability of the U.S. roadway system arise from a desire to keep the public safe, make emergency response and recovery easier, and reduce economic loss and social upheaval. Many common issues concerning earthquake risk and transportation system components, particularly bridges, are addressed in this paper. For roadway systems, there are three aspects of seismic risk to take into consideration: earthquake probability, structural vulnerability, and possible repercussions [3]. Many remote and volcanic places already have seismic warning systems in place, which might lead to an increase in the number of people expecting to survive an earthquake. Many study findings also add to our understanding of the features of earthquakes and their effects on the surrounding environment. Additionally, machine learning has been utilized to improve the accuracy of information and forecasting outcomes.

International Journal of Engineering, Science and Mathematics
Vol. 8 Issue 6, June 2019, ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: ijesmj@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

Because of a paucity of data or a lack of a proper approach for making predictions in machine learning, some results are inaccurate and raise false alarms [4,5,6]. We still have a lot of room to grow in our understanding of earthquake prediction, so we can get better outcomes and more confidence out of it. In addition, a realistic and accurate forecast would allow for better management of the evacuation route course, which might lower the number of fatalities.

III. LITERATURE REVIEW

A. Machine learning

Through the use of certain algorithms, machine learning is able to gain insight from a single dataset or a collection of datasets. Three machine learning methods, namely Naive Bayes, SVM, and multinomial regression, are evaluated in this study. SVM beats other algorithms that forecast earthquake location based on Magnitude and Depth when utilizing 10 years of data without grouping. SVM uses just latitude and longitude as a component in this prediction [7]. A set of tasks known as supervised learning include training a system how to approximatively translate data input to outputs data using a variety of input-output instances. To test its accuracy, the model is fed new data that it has never seen before, and its predictions are based only on its prior experience with the training data. Classification or regression may be used to address this issue [8,9]. Using regression, we can learn to predict a continuous label in a controlled environment. Supervised learning includes making predictions about the classes in which data will be grouped (a discrete target). Any dimension, any data type, such as a number, time - series data, or a graphic may be a data input factor in a predictive data mining application. Learning tasks that employ an ML model to explain or extract connections from data fall under the unsupervised category. There are no outputs or targets while using unsupervised learning.

B. The Prediction and Forecasting of Earthquakes

There are several antecedents that may precede a significant earthquake that may be used to forecast the "when, where, and size" of an impending disaster. The "foreshock–mainshock–aftershock" pattern is well-known for its ability to anticipate and track an earthquake with foreshocks and aftershocks [9,10]. It is considered that the collapse of tiny frictional areas at or near where a mainshock would occur is what causes foreshocks throughout earthquake nucleation, as the fault starts to break. An enormous number of scientists have investigated precursors both within and outside of the laboratory, using computer models and actual samples from the Earth. With a few noteworthy instances when moderate earthquakes have been recorded before massive subduction earthquakes, seismic precursors are not regularly observed in Earth while being common in laboratory research and simulations

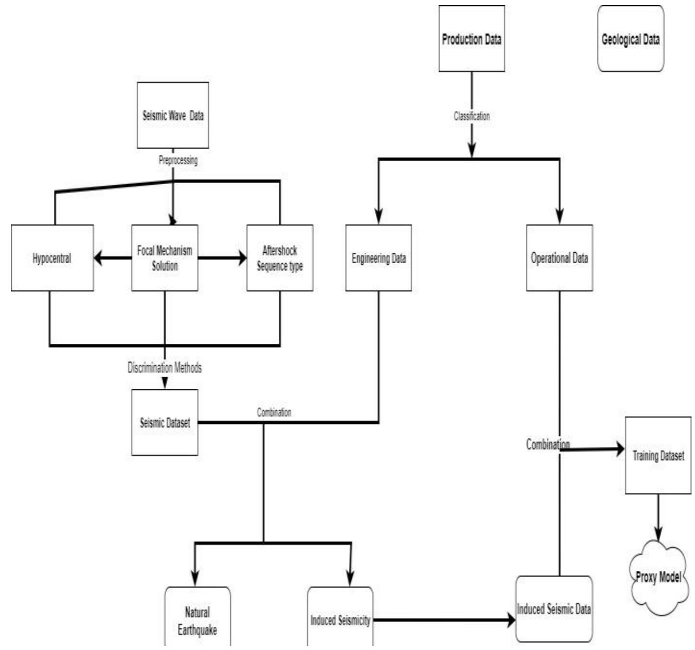

Fig i: Geological data analysis process for seismic analysis

A list of key antecedents was really requested by the International Association for Seismology and Physics of the Earth's Interior in the early 1990s [12]. The International Commission on Earthquake Forecasting for Civil Protection concluded in 2011 that there was "much opportunity for methodological improvements," which is definitely an understatement after conducting a thorough examination of the scientific literature. Many claimed antecedents were found to be inconsistent and inappropriate for statistical analysis, according to the study. As published data tend to favorable outcomes, it's difficult to estimate the number of false negatives, or earthquakes that didn't show any warning signs before they struck. Precursory phenomena have a low rate of false positives;however, this is seldom measured [12].

In addition, there is a wide-ranging and acrimonious debate going on about the nature of fault rupture, namely the question of whether or not earthquakes can be predicted. Predicting earthquakes in advance may be conceivable if faults slide in an absolutely predictable fashion; if they slip stochastically, anticipating the immediate aftermath of a collapse may be possible but not long before. Overall, we are far from being able to anticipate earthquakes with any degree of accuracy, but new work on laboratory quakes provides some optimism.

C. Earthquake Science Using Machine Learning

In the recent two decades, machine learning (ML) applications in geoscience have grown fast. These new ML algorithms, fast and affordable graphics processing units, and the abundance of enormous, frequently continuous datasets have fuelled this revolution in data-driven analysis." [12,13] Due to this fast growth, current and new machine learning technologies have been applied to a variety of geoscientific issues. These challenges include geological formation identification, reservoir characterization, seismic wave detection and phase identification and location, earthquake early warning, volcano monitoring, tomographic imaging, and more. There has been a lot of work over the last five years to use these methodologies to understand and predict fault physics and failure.

D. Earthquake Prediction with ML

.

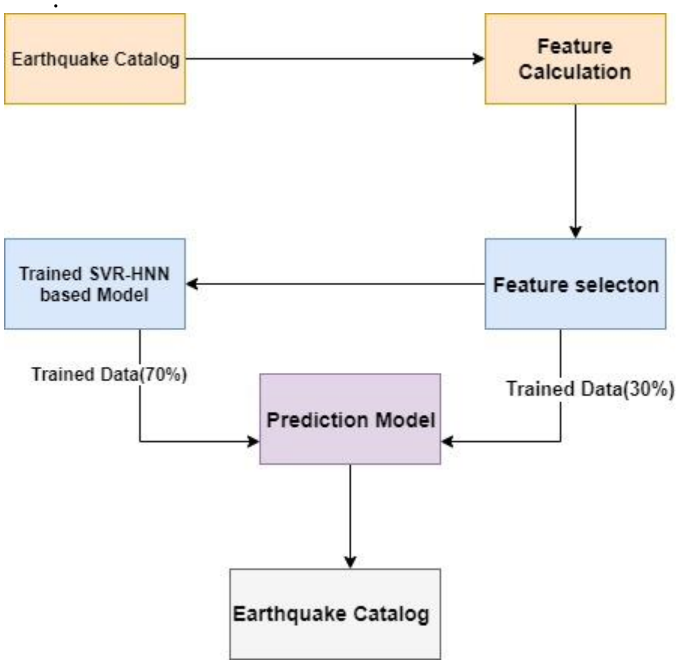

Fig i: Earthquake prediction model for geotechnical analysis

The analysis of the features of a continuous seismic signal transmitted from a fault shear zone proved to be the first successful attempt at earthquake forecasting using ML. A decision tree-based ML model is used in the random forest technique to forecast earthquakes [13].Two granular fault gouge-containing faults were concurrently sheared at a predefined shear velocity and a constant normal load in the study. The equipment monitored mechanical information such as the shear stress, movement of the shearing blocks, the size of the gouge layer, the applied load, and friction. Additionally, piezoceramics implanted in the lateral plates of the shear arrangement have been used to capture continuous recordings of seismic wave radiation from the fault zone. The faults in the lab fail in cycles of sticking and slipping that are similar to the way tectonic faults load and break during earthquakes [14]. Predicting failure time is only possible with a snapshot taken during shear of the continuous seismic signals. There were three different decision tree models that were constructed in order to forecast the shear displacement, shear stress, and gouge thickness. Model-based approaches are used for each of these variables: shear stress (independent ML models), displacement (independent ML models), gouge thickness (independent ML models) [14,15]. It is based on the device's shear stress indication that the time to failure may be determined. Data from both the input and the output are included into the ML model during the training phase. The model only sees the seismic data while it is being tested, thus the recorded shear stress is considered to be the ground truth; the model did not observe this stress when it was being tested [16].

IV. SIGNIFICANCE TO THE U.S

In terms of protecting lives and property, earthquake risk forecasts are very valuable. 'Earthquake risk prediction' Natural earthquakes, mine explosions, nuclear testing, and other types of seismic activity may all be used to anticipate large earthquakes, according to some scientists. Earthquake engineering is a branch of civil engineering that focuses on minimising the hazards associated with earthquakes [17]. Structural and seismological engineering, as well as risk and decision analysis and probability and reliability theory, are used to comprehensively manage infrastructure performance in the face of an unknown future of earthquakes. Complex issues, computing efficiency, propagation and treatment of uncertainty, and ease of decision-making are some of the benefits of ML over conventional techniques [18]. Not only has machine learning (ML) matured, but so have other scientific and technical domains, including materials research, project management, and geotechnical engineering. An attribute matrix with four distinct categories, such as ML technique, subject area, data resource, and size of analysis, will be used in the future to organize the current literature. The state-of-the-art evaluation provides an indication of the degree to which ML has been implemented in four different subject areas of earthquake engineering. These subject areas include earthquake risk prediction, dynamical systems and environmental monitoring, seismic risk analysis, and structural response for earthquake mitigation.

V. FUTURE IN THE U.S.

The geoscience field will exploit earthquake prediction using Machine learning in the U.S. as an introduction to machine learning (ML), a challenge in which to practice using various ML techniques, and as a teaching tool in ML courses. Students and academics have utilized the top five techniques to contrast the subtleties of rival ML techniques and to attempt to modify and enhance the strategies for different purposes. High-performance computing systems are also needed to test novel techniques and put them into practice in new industries. The liquefaction machine learning model is still being improved by the researchers [18]. According to the researchers, further study is required to build machine learning models that can be applied to various earthquakes and geologic situations. As part of their work, earthquake investigators will concentrate on identifying the processes that lead to structural failure or collapse, as well as planning and mitigating earthquake risk by implementing the best repair plans, performance-based improvements, and specialized solutions possible. Property owners, insurance companies, law firms, and governmental organizations may all count on us for comprehensive assistance in the wake of an earthquake as well as in the preparation and mitigation stages leading up to one.

VI. CONCLUSION

This study described how to assess how machine learning may be used to forecast earthquakes. Research reveals that ML has infiltrated earthquake engineering, allowing researchers and decision makers to lessen the impact of seismic risks on civil constructions. The results. Engineers working in earthquake engineering use a wide range of disciplines to explain earthquake hazard, analyze structure reaction, evaluate seismic risk, as well as assess seismic protection systems. This is an interdisciplinary engineering area. ML algorithms have been used in a variety of ways in each subject. An earthquake-safe constructed environment is the result of the combined efforts of environmental experts, geotechnical engineers, construction companies, and public officials. Structure engineering, which includes the design and construction of structures, and the anchoring of non-structural building contents, is a crucial element of this endeavor and the emphasis here. There are several ways to reduce the potential for human and economic damage from a maximum probability earthquake at a specific location, such as structural analyses and targeted retrofitting of existing structures. A case study on the relationship between science, technology, and ethics may be found in earthquake engineering.

REFERENCES

[1] K. Ghaedi, "Earthquake Prediction," in *Earthquakes - Tectonics, Hazard and Risk Mitigation*. InTech, 2017. Available: https://doi.org/10.5772/65511

[2] A. Hoque, J. Raj, and A. Saha, "Approaches of Earthquake Magnitude Prediction Using Machine Learning Techniques," *SSRN Electronic Journal*, 2018. Available: https://doi.org/10.2139/ssrn.3513365

[3] K. M. Asim, F. Martínez-Álvarez, A. Basit, and T. Iqbal, "Earthquake magnitude prediction in Hindukush region using machine learning techniques," *Natural Hazards*, vol. 85, no. 1, pp. 471–486, Sep. 2016. Available: https://doi.org/10.1007/s11069-016-2579-3

[4] J. Kruppa, A. Ziegler, and I. R. König, "Risk estimation and risk prediction using machine-learning methods," *Human Genetics*, vol. 131, no. 10, pp. 1639–1654, Jul. 2012. Available: https://doi.org/10.1007/s00439-012-1194-y

[5] E. W. Steyerberg, T. van der Ploeg, and B. Van Calster, "Risk prediction with machine learning and regression methods," *Biometrical Journal*, vol. 56, no. 4, pp. 601–606, Feb. 2014. Available: https://doi.org/10.1002/bimj.201300297

[6] H. Adeli and X. Jiang, "Dynamic Fuzzy Wavelet Neural Network Model for Structural System Identification," *Journal of Structural Engineering*, vol. 132, no. 1, pp. 102–111, Jan. 2006. Available: https://doi.org/10.1061/(asce)0733-9445(2006)132:1(102)

[7] P. A. Mastorocostas and J. B. Theocharis, "A recurrent fuzzy-neural model for dynamic system identification," *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)*, vol. 32, no. 2, pp. 176–190, Apr. 2002. Available: https://doi.org/10.1109/3477.990874

[8] A. H. Alavi and A. H. Gandomi, "Prediction of principal ground-motion parameters using a hybrid method coupling artificial neural networks and simulated annealing," *Computers & Structures*, vol. 89, no. 23-24, pp. 2176–2194, Dec. 2011. Available: https://doi.org/10.1016/j.compstruc.2011.08.019

[9] E. E. R. Institute, *Learning from earthquakes: Planning guide*. Oakland, Calif: The Institute, 1977.

[10] M. Fragiadakis, N. D. Lagaros, Y. Tsompanakis, and M. Papadrakakis, "Improved Seismic Design Procedures and Evolutionary Tools," in *Intelligent Computational Paradigms in Earthquake Engineering*. IGI Global, 2007, pp. 1–21. Available: https://doi.org/10.4018/978-1-59904-099-8.ch001

[11] R. O. Foschi, "Applying Neural Networks for Performance-Based Design in Earthquake Engineering," in *Intelligent Computational Paradigms in Earthquake Engineering*. IGI Global, 2007, pp. 22–41. Available: https://doi.org/10.4018/978-1-59904-099-8.ch002

[12] A. Alimoradi, S. Pezeshk, and C. Foley, "Evolutionary Seismic Design for Optimal Performance," in *Intelligent Computational Paradigms in Earthquake Engineering*. IGI Global, 2007, pp. 42–58. Available: https://doi.org/10.4018/978-1-59904-099-8.ch003

[13] E. Salajegheh and A. Heidari, "Optimum Design of Structures for Earthquake Induced Loading by Wavelet Neural Network," in *Intelligent Computational Paradigms in Earthquake Engineering*. IGI Global, 2007, pp. 80–100. Available: https://doi.org/10.4018/978-1-59904-099-8.ch005

[14] F. Ali and A. Ramaswamy, "Developments in Structural Optimization and Applications to Intelligent Structural Vibration Control," in *Intelligent Computational Paradigms in Earthquake Engineering*. IGI Global, 2007, pp. 101–121. Available: https://doi.org/10.4018/978-1-59904-099-8.ch006

[15] B. Osher, "Statistical Estimation of the Maximum Magnitude and its Uncertainty from a Catalogue Including Magnitude Errors," in *Earthquake Hazard and Risk*. Dordrecht: Springer Netherlands, 1996, pp. 25–37. Available: https://doi.org/10.1007/978-94-009-0243-5_3

[16] H. Aslani, C. Cabrera, and M. Rahnama, "Analysis of the sources of uncertainty for portfolio-level earthquake loss estimation," *Earthquake Engineering & Structural Dynamics*, vol. 41, no. 11, pp. 1549–1568, Jul. 2012. Available: https://doi.org/10.1002/eqe.2230

[17] U. S. N. B. o. Standards, *Potential systems for lead hazard elimination: Evaluations and recommendations for use*. Washington: The Bureau, 1973.

[18] C. Taylor, N. Uddin, Y. (. Lee, K. Yu, C. Poland, and W. Graf, "The 2008 Sichuan Earthquake in China and Implications for the Central United States," in *Seismic Hazard Design Issues in the Central United States*. Reston, VA: American Society of Civil Engineers, 2014, pp. 35–49. Available: https://doi.org/10.1061/9780784413203.ch04