BIBECHANA
Vol. 22, No. 1, April 2025, 22-29

ISSN 2091-0762 (Print), 2382-5340 (Online)
Journal homepage: http://nepjol.info/index.php/BIBECHANA
Publisher:Dept. of Phys., Mahendra Morang A. M. Campus (Tribhuvan University)Biratnagar

Machine learning for predicting earthquake magnitudes in the Central Himalaya

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Abstract

Human intervention cannot halt natural disasters like earthquakes, but machine learning applications expertise can be utilized to detect patterns in data and increase understanding and predictive power. Recent development of machine learning models has increasingly developed interest in forecasting and predicting the magnitude of earthquakes. In this work, Random Forest Regressor (RFR), Multi-Layer Perceptron Regressor (MLPR), and Support Vector Regression (SVR) models were employed to predict the magnitude of greater than 6 mb earthquakes that occurred in the year 2015 in the central Himalaya. We noticed RFR method had been able to predict the magnitude of the Gorkha earthquake (6.9 mb), the Kodari earthquake (6.7 mb), and 6.5 mb magnitude earthquake (aftershock of Gorkha earthquake) in comparison with the other two models. We also checked the performance of these models by three parameters Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) and noticed the better performance of RFR model. The findings illustrate that RFR is achieving better performance than the other two algorithms, as the predicted magnitudes are close to the actual magnitudes.

Keywords
Machine Learning, Earthquake, Regressor, Prediction.

Article information
Manuscript received: October 6, 2024; Revised: January 7, 2025; Accepted: January 12, 2025
DOI https://doi.org/10.3126/bibechana.v22i1.70637

1 Introduction

An earthquake is a natural disaster that strikes suddenly, between seconds to minutes, and shakes a large area of landmass, potentially killing people and damaging property. Nepal, which is positioned in the center of the Himalayan arc, saw many small and large earthquakes in last millennia [1–5]. The seismic activity in the Himalayan region is impacted by the buildup of strain energy that happened roughly 50 million years ago during the Indian plate's thrust beneath the Eurasian plate [6–8].

The region has had more recent earthquakes in the past 70 years, including the 1988 Udayapur earthquake of magnitude 6.6 Mw, 2011 Sikkim earthquake of magnitude 6.9 Mw, 2015 Gorkha earthquake of magnitude 7.9 Mw, Dolakha (Kodari) earthquake of magnitude 7.3 Mw, Doti earthquake of magnitude 6.6 ML, and the 2023 Jajarkot earthquake of magnitude 6.4 ML [8–10].

Human intervention cannot halt natural disasters like earthquakes, but machine learning application expertise can be utilized to detect patterns in data and increase understanding and predictive power [11–13]. Most of the machine learning (ML) algorithms fall into one of two categories: Supervised Learning (SL) and Unsupervised Learning (USL) (Figure 1).

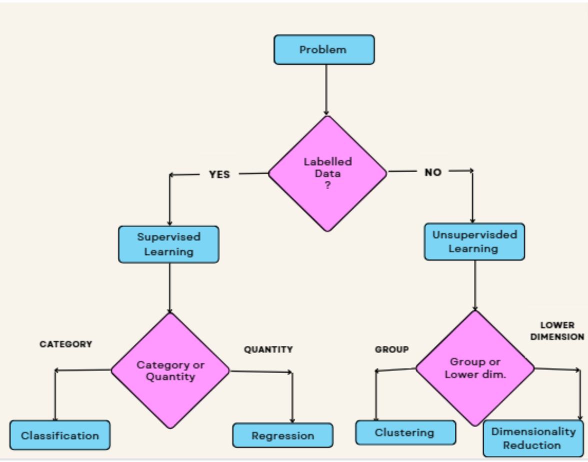

Figure 1: Basic idea of selecting the ML algorithms. Unsupervised ML for unlabelled data, and supervised ML for labelled data.

In SL, the computer is instructed or trained with the labeled data. SL algorithms construct two types of predictive models, Regression and Classification models which approaches data in a different way. For forecasting a numerical value, regression model is used. USL includes utilizing an unlabeled dataset to train the computer, after which it uses its own judgment to anticipate outputs. The primary goal of unsupervised learning is to categorize or group the unsorted dataset according to similarities, differences, and patterns. The machines are to find the hidden patterns in the input dataset [14].

In contrast to traditional methodologies, machine learning (ML) models offer a fresh and creative way to find hidden signals and patterns. This development covers a wide range of seismic applications, such as earthquake detection and phase identification, early warning systems, ground motion prediction, seismic tomography, earthquake geodesy, seismic risk assessment, and finally earthquake prediction [15, 16].

It is generally accepted that there isn't a single ideal algorithm or machine learning solution that works for all situations and datasets because algorithm performance varies on a variety of parameters. While some algorithms work better with tiny amounts of data, others are more effective with large samples of data. While some algorithms just need quantitative inputs, others demand categorical inputs. The complication of the data and the number of features that the model needs to understand and make predictions are crucial factors when picking an algorithm. To account for this, three distinct algorithms namely, Random Forest Regressor (RFR), Support Vector Regressor (SVR), Multi-Layer Perceptron Regressor (MLPR) have been used in this work to analyse an earthquake dataset [17]. Different hyper parameters have been looked at for each model that has been selected, and the predicted results have been equitably assessed with metrics like Mean Square Error (MSE), Root Mean Square (RMSE and Mean Absolute Error (MAE).

1.1 Random Forest

A random forest algorithm builds a forest from many separate decision trees, and chooses the outcome based on the predictions offered by them. The decision nodes, leaf nodes, and root nodes make up a decision tree (Figure 2).

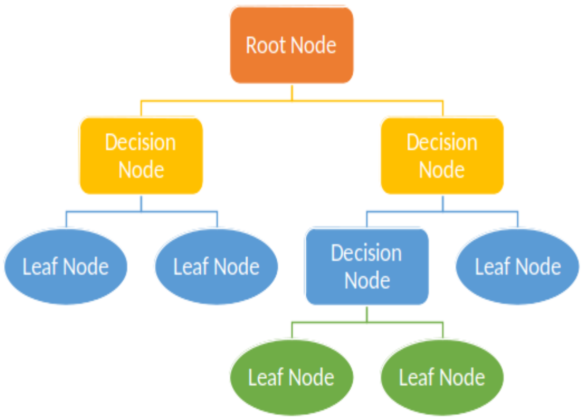

Figure 2: Schematic presentation of Random Forest algorithm.

Decision trees are trained using knowledge acquisition. A method splits a training dataset into branches, and then further divides those branches until a leaf node is reached [18]. Splitting branches during the creation of decision trees depends on entropy and information gain. The attributes used to forecast the outcome are represented by the nodes in the decision tree.

1.2 Support Vector Regression

A Support Vector Regressor (SVR) is a mathematical framework designed to function as a method or strategy for optimizing a particular mathematical function concerning a provided dataset. The SVR method focuses on finding the ideal hyperplane in the feature space (N-dimensional space) which in turns divides the data points into various classes [19]. The hyperplane seeks to make the distance between the closest points of various classes as large as feasible. The size of the hyperplane is determined by the quantity of features. For two input characteristics, the hyperplane essentially becomes a line whereas it turns into a 2-D plane for three input characteristics.

1.3 Multi-Layer Perceptron Regression

A Multi-Layer Perceptron regression (MLPR) consists of at least three layers: an input layer, a hidden layer, and an output layer. Every layer makes use of the results from the layer before it. Without input, each layer node is referred to as a neuron. The primary processing unit of the neural network, the neuron, gathers data from a variety of inputs, applies weights and bias terms, and then sends the final product to an active function that produces outputs [20]. A multilayer perceptron model primarily comprises of a back propagation model for training, and additionally, it employs a linear activation function in its hidden layers, which, when combined with multiple layers, allows it to approximate non-linear relationships in the data.

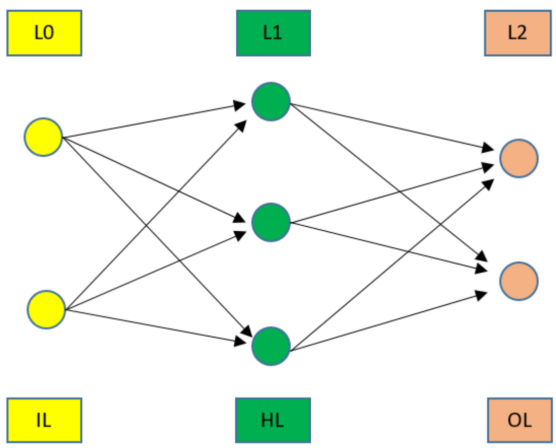

Figure 3: Schematic presentation of Multilayer Perceptron algorithm where L0 stands for (Layer 0) or Input Layer (IL), L1 stands for (Layer 1) or Hidden Layer (HL), and L2 stands for (Layer 2) or Output Layer (OL).

The study area is in the central Himalaya region between latitudes of 26.5° and 30.5° and longitudes of 80° and 88°, which includes the entirety of Nepal along with certain regions of India and China. The region has low to moderate seismicity (Figure 4). The seismicity of the region is primarily controlled by the Main Central Thrust (MCT), Main Boundary Thrust (MBT), Main Frontal Thrust (MFT), and several small faults that are trending north to the south [21–23].

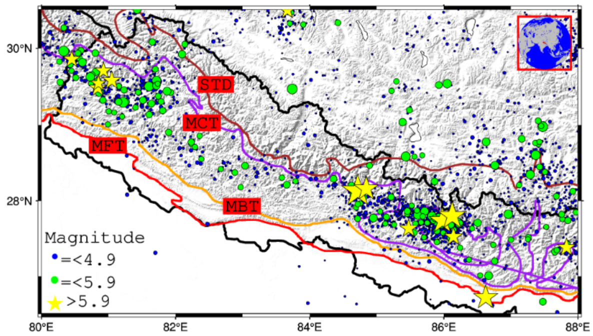

Figure 4: Seismicity of the study area. Also showing major Himalayan thrusts STD, MCT, MBT, and MFT from north to south, namely South Tibetan Detachment System, Main Central Thrust, Main Boundary Thrust, Main Frontal Thrust.

The earthquake occurrence mechanisms are widely regarded as unpredictable and marked by non-linear behaviors. Most ongoing research in the field of ML has concentrated on exploring how neural networks can be applied to address this challenge [11,24,25]. Because of conceptual, algorithmic, and computational constraints, it was challenging to construct efficient models via the early explorations, but it is now possible to use advanced models by leveraging Deep Neural Networks (DNNs) [13,26].

While going through the literature, Artificial Neural Network (ANN) in collaboration with seismic precursors were found useful to predict earthquakes. For example, Back Propagation Neural Network (BPNN) models have been used to identify unusual behaviour in radon concentrations produced by earthquakes [27]. From the assembly of Radial Basis function (RBF) neural networks, earthquakes in China have been predicted (Y. Liu et al., 2004). Analysing seismic events over a period in southern California and San Francisco, a model was designed, based on ANNs which can predict the earthquakes on monthly basis [16]. In 2009, the identical seismic considerations were incorporated with the Probabilistic Neural Network (PNN) to predict earthquake [15].

The work [28] demonstrates that, although the occurrence of earthquakes is nonlinear and random phenomena, it is still possible to model it using methodologies of machine learning. The neural network-based method for predicting earthquakes was evaluated using data from the Portuguese region of the Azores, and the results showed that it successfully predicted earthquakes in July 1998 for the modified Mercalli intensity (MMI) of 8, and in January 2004 for the modified Mercalli intensity (MMI) of 5, respectively [29]. According to studies [15, 16] probabilistic neural networks (PNNs) may be used for small and intermediate earthquake prediction while recurrent neural networks (RNNs) may be utilized for earthquakes of large magnitude. According to a comparative study employing ANN technology and non-linear predictability assessments, the dynamics of earthquakes in the North-East India region were found to be stochastically scaled process [30]. In a study conducted in Hindukush region by the application of four machine learning algorithms on a temporal distribution of past earthquakes, the accuracy to predict the earthquakes is noticed to be 65% on Linear Programming Boost Ensemble while 58% and 62% for RNN and Random Forest [31].

The aim of this study is to utilize historical seismic data, including date, time, latitude, and longitude to create predictive algorithms that can predict the magnitude and compare it with the actual magnitude of the earthquakes in central Himalayan region. The primary challenge is to design and train machine learning models that enhances our ability to predict earthquake magnitudes accurately, aiding in disaster preparedness and response efforts.

2 Data and Methodology

This research is quantitative and based on quantitative earthquake data like magnitude, latitude, longitude, and focal depth. The data extracted from the International Seismological Centre (ISC) catalog for the period between February 1, 1964, and December 27, 2022 [32], included additional entries such as event identification numbers, author names, station codes, and phase data, which were deemed irrelevant for this study and excluded. The catalog was further processed to identify missing values in critical attributes like magnitude, depth, latitude, and longitude, with incomplete records removed. The final dataset comprises 2595 earthquakes, with magnitudes ranging from 2.9 to 6.9. After compilation, the data was thoroughly cleaned, formatted, and stripped of missing or damaged entries to ensure its suitability for analysis. The three models, namely Random Forest Regressor (RFR), Multi-Layer Perceptron Regressor (MLPR), and Support Vector Regressor (SVR) are selected over others for their proven capability to manage the inherent complexities of the dataset, such as non-linearity, high-dimensionality, and data noise [33, 34]. The data processing in this study involves configuring key hyper parameters across these models. For RFR, bootstrapping is enabled (bootstrap=True), and the model uses all features for each split (max_features=1.0), with trees growing until leaves are pure or contain fewer than 2 samples (min_samples_split=2). It employs the 'squared_error' criterion to minimize mean squared error and uses 100 trees (n_estimators=100).

The MLPR is configured with the 'tanh' activation function, a learning rate of 0.001 (learning_rate_init=0.001), and 500 neurons in the hidden layer (hidden_layer_sizes=500), utilizing the 'sgd' solver for optimization. It runs without early stopping (early_stopping=False) and continues until reaching the maximum number of iterations (max_iter=100). The SVR model uses an RBF kernel (kernel='rbf') with a regularization parameter (C=1.0) and an epsilon of 0.1 to control error margin, while gamma is set to 'auto'. All models are trained with random_state=0 for reproducibility, and verbose output is suppressed (verbose=False). These configurations collectively guide the data through preprocessing, transformation, and optimization steps to ensure that the machine learning models are effectively trained and evaluated.80% of the dataset was provided for training and the remaining 20% for testing, allowing for proper model evaluation on unseen data (Aryal et al., 2024). Thereafter, numerical optimization algorithms are employed to iteratively fine-tune the model parameters using a cost function. To evaluate the model's performance, we calculate metrics such as Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). Finally, the machine learning model is employed to handle new data.

3 Results and Discussion

Machine learning offers promising capabilities for analyzing historical data to predict earthquake magnitudes, a task with no definitive method yet. This research leverages data from 2595 seismic events and applies Random Forest Regressor (RFR), Support Vector Regressor (SVR), and Multi-Layer Perceptron Regressor (MLPR). These models were chosen for their ability to handle non-linear relationships and complex geophysical patterns: RFR for robustness and feature analysis, SVR for modeling nonlinearities with kernel methods, and MLPR for capturing intricate dependencies. Their selection is supported by their proven reliability in similar seismological studies [33–35]. We have tested these methods to forecast the magnitude of the earthquakes that hit the central Himalaya region in the year 2015 and comparison between actual magnitude and predicted magnitude are depicted by the different plots. The density magnitude plot of the dataset is depicted by Figure 5.

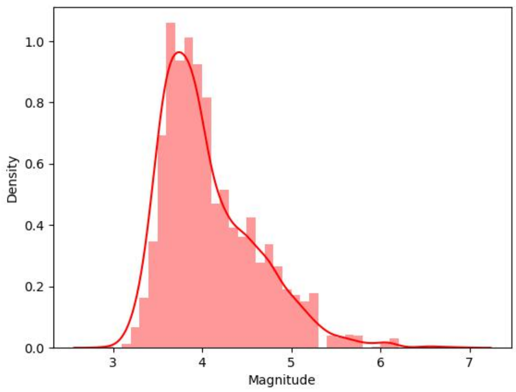

Figure 5: A density magnitude plot provides a visual representation of the frequency of earthquakes at different magnitudes.

The Y-axis represents the density of earthquakes, often measured as the number of earthquakes per unit magnitude. This shows how frequently earthquakes of different magnitudes occur within the dataset. It tends to have a higher density for smaller magnitude earthquakes and gradually decreases as the magnitude increases. A single higher peak in the plot suggests that 3.1 to 5.4 magnitudes are predominant in that region. The plot shows a steep decrease in density as magnitude increases which suggests that there are fewer large earthquakes, a typical characteristic of most seismically active regions.

Five earthquakes of the year 2015, namely the Gorkha earthquake (6.9 mb), the Kodari earthquake (6.7 mb), the magnitude 6.1 mb earthquake, the magnitude 6.5 mb earthquake and the magnitude 6.6 mb earthquake of diverse locations, are used to assess the performance of the proposed techniques. The RFR, MLPR, SVR models are trained and tested through multiple cycles to refine their performance which helps to get the minimum errors [33,34,36,37]. Table 1 gives the predicted magnitude and actual magnitude of above-mentioned earthquakes and heat map of predicted magnitude is presented in Figure 6.

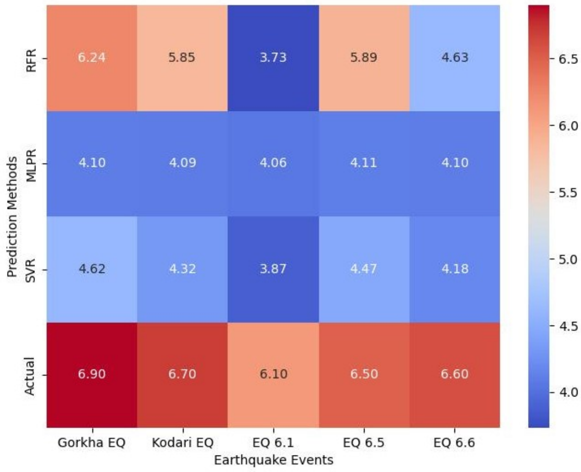

Figure 6: A heat map of magnitude predicted by Random Forest (RFR), Multi-Layer Perceptron (MLPR), Support Vector Regression (SVR) for the Gorkha earthquake, the Kodari earthquake, the magnitude 6.1 earthquake, the magnitude 6.5 earthquake and the magnitude 6.6 earthquake.

Following the training phase, the model is validated to forecast the earthquake exceeding 6.0 in mb scale and the 3d plot of the predicted magnitude and actual magnitude plot are depicted by Figure 7.

Table 1: Predicted and actual magnitude of the earthquakes.

Name	RFR based magnitude	MLPR based magnitude	SVR based magnitude	Actual magnitude
Gorkha EQ	6.24	4.09694	4.61592	6.9
Kodari EQ	5.846	4.08975	4.32297	6.7
EQ6.1	3.732	4.06169	3.86912	6.1
EQ6.5	5.887	4.10614	4.47054	6.5
EQ6.6	4.629	4.09994	4.18434	6.6

Table 2: Adapted machine learning model with error and accuracy.

Model	MAE	MSE	RMSE	Accuracy of Model
Random Forest Regressor (RFR)	0.36	0.23	0.48	0.16
Multi-layer Perceptron Regressor (MLPR)	0.40	0.27	0.52	0.016
Support Vector Regressor (SVR)	0.35	0.24	0.49	0.13

The magnitude predicted by RFR is close to the actual magnitude of the Gorkha earthquake, the Kodari earthquake, and the magnitude 6.5 aftershock (above 6.0 for both events) while the magnitude predicted for other earthquakes deviates from the actual value (Figure 7). The magnitude predicted by SVR significantly deviates from the actual values, as it predicts 4.61592 for the Gorkha earthquake and 4.32297 for the Kodari earthquake. The magnitude predicted by MLPR is just around 4 and almost the same for all five earthquakes and greatly deviated from the actual magnitudes.

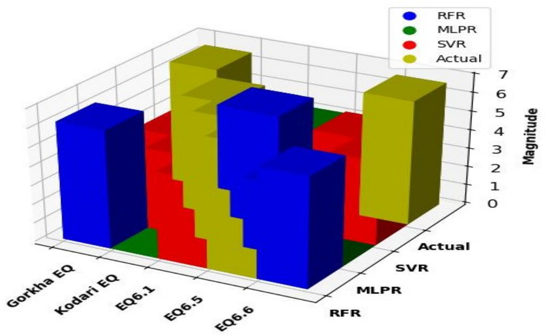

Figure 7: 3D plot of predicted magnitude versus actual magnitude for the Gorkha earthquake, the Kodari earthquake, the magnitude 6.1 earthquake, the magnitude 6.5 earthquake, and the magnitude 6.6 earthquake using RFR, MLPR, SVR.

3.1 Performance Evaluation

The performance of RFR, SVR, and MLPR is presented in Table 2 and Figure 8 and their accuracies are presented in Figure 9.

The 3D error bar in Figure 8 depicts the errors produced by RFR, MLPR, and SVR models. The MAE, MSE, and RMSE errors for RFR (0.36, 0.23, 0.48) and SVR (0.35, 0.24, 0.49) exhibit minimal disparity, whereas MLPR's errors are marginally elevated (0.40, 0.27, 0.52). These findings indicate that MLPR's performance is comparatively inferior to that of RFR and SVR.

The RFR model demonstrates superior performance in predicting earthquake magnitudes compared to the other two methods. The accuracy plot reveals that RFR achieves a slightly higher accuracy (0.16) than SVR (0.13) and MLPR (0.016) (Figure 9). This can be attributed to RFR's ensemble approach, which leverages decision trees to capture complex patterns in the data effectively. In contrast, SVR prioritizes a smoother fit by minimizing margin violations, which may limit its ability to capture intricate details. The notably low accuracy of the MLPR model suggests that it fails to learn meaningful patterns from the data, leading to predictions that are essentially random.

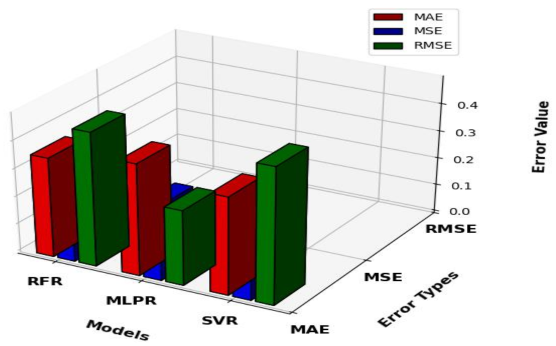

Figure 8: 3D error bar of three different methods employed for the estimation of the magnitudes.

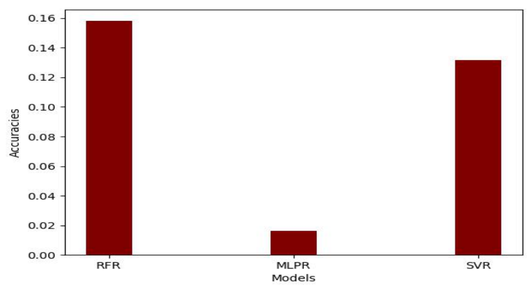

Figure 9: Accuracy bar of three different methods used for the estimation of magnitudes.

4 Conclusion

Three machines learning algorithms namely, Random Forest Regressor (RFR), Multi-layer Perceptron (MLPR), and Support Vector Regressor (SVR) have been used to predict the major earthquake events that occurred in the year 2015. The study has been applied to 2595 earthquakes of magnitude range 2.9 to 6.9, collected from ISC catalog, for 68 years. The results suggest that all algorithms, while providing reasonable estimates, tend to under predict earthquake magnitudes, particularly for higher-magnitude events. For example, the RFR model predicts 6.24 for Gorkha earthquake (actual 6.9) and 5.85 for Kodari earthquake (actual 6.7), indicating that it tends to slightly underestimate magnitudes. Similarly, the MLPR model under predicts with values like 4.10 for Gorkha earthquake, while the SVR model also provides lower predictions, such as 4.62 for Gorkha earthquake. Among three algorithms RFR is found to be the superior as it estimates the magnitude close to actual magnitude. This highlights the need for further model refinement through hyper parameter tuning, feature engineering, or incorporating more detailed seismic data to enhance prediction accuracy, especially for larger earthquakes. Analyzing the residuals between predicted and actual values could help identify areas where the models are underperforming and guide improvements.

From the error perspective both RFR and SVR do not show significant differences but as the prediction pattern is observed RFR shows the better promises. Despite challenges such as imbalanced datasets, uncertainties in seismic features, and the complexity of modeling dynamic, non-linear relationships in earthquake patterns, the results of this study indicate that both the Random Forest Regressor (RFR) and Support Vector Regressor (SVR) hold promise for prediction, particularly when large datasets are available.

Acknowledgments

One of the authors (RKT) would like to acknowledge the Research Management Cell (RMC), Birendra Multiple Campus, Tribhuvan University, Nepal for providing financial support.

References

[1] R. V. Almeida, J. Hubbard, L. Liberty, A. Foster, and S. N. Sapkota. Seismic imaging of the main frontal thrust in nepal reveals a shallow décollement and blind thrusting. *Earth and Planetary Science Letters*, 494:216–225, 2018.

[2] M. Hubbard, M. Mukul, A. P. Gajurel, A. Ghosh, V. Srivastava, B. Giri, N. Seifert, and M. M. Mendoza. Orogenic segmentation and its role in himalayan mountain building. *Frontiers in Earth Science*, 9, 2021.

[3] K. M. Khattri and A. K. Tyagi. Seismicity patterns in the himalayan plate boundary and identification of the areas of high seismic potential. *Tectonophysics*, 96(3–4):281–297, 1983.

[4] M. Nayak and T. G. Sitharam. Estimation and spatial mapping of seismicity parameters in western himalaya, central himalaya and indogangetic plain. *Journal of Earth System Science*, 128(3), 2019.

[5] R. K. Tiwari. *Multifractal Approach To the Study of Gorkha Earthquake of 25 April, 2015 Nepal*. PhD thesis, Institute of Science Technology, Tribhuvan University, 2023.

[6] A. K. Dubey. *Understanding an Orogenic Belt*. Springer, 2014.

[7] J. F. Ni. Active tectonics of the himalaya. *Proceedings of the Indian Academy of Sciences - Earth and Planetary Sciences*, 98(1):71–89, 1989.

[8] R. K. Tiwari and H. Paudyal. Geodynamics of gorkha earthquake (mw 7.9) and its aftershocks. *Himalayan Physics*, 9:103–109, 2020.

[9] G. Monsalve, A. Sheehan, V. Schulte-Pelkum, S. Rajaure, M. R. Pandey, and F. Wu. Seismicity and one-dimensional velocity structure of the himalayan collision zone: Earthquakes in the crust and upper mantle. *Journal of Geophysical Research: Solid Earth*, 111(10):1–19, 2006.

[10] R. K. Tiwari and H. Paudyal. Spatial mapping of b-value and fractal dimension prior to november 8 , 2022 doti earthquake, nepal. *PLOS ONE*, 18(8):1–13, 2023.

[11] M. H. Al Banna, K. A. Taher, M. S. Kaiser, M. Mahmud, M. S. Rahman, A. S. M. S. Hosen, and G. H. Cho. Application of artificial intelligence in predicting earthquakes: State-of-the-art and future challenges. *IEEE Access*, 8:192880–192923, 2020.

[12] M. Aryal, R. K. Tiwari, and H. Paudyal. Prediction of earthquakes in nepal and the adjoining regions using lstm. *BMC Journal of Scientific Research*, 7:12–26, 2024.

[13] P. M. R. DeVries, F. Viégas, M. Wattenberg, and B. J. Meade. Deep learning of aftershock patterns following large earthquakes. *Nature*, 560(7720):632–634, 2018.

[14] S. Shalev-Shwartz and S. Ben-David. *Understanding machine learning: From theory to algorithms*. Cambridge University Press, 2014.

[15] H. Adeli and A. Panakkat. A probabilistic neural network for earthquake magnitude prediction. *Neural Networks*, 22(7):1018–1024, 2009.

[16] A. Panakkat and H. Adeli. Neural network models for earthquake magnitude prediction using multiple seismicity indicators. *International Journal of Neural Systems*, 17(1):13–33, 2007.

[17] G. Asencio-Cortés, F. Martínez-Álvarez, A. Troncoso, and A. Morales-Esteban. Medium–large earthquake magnitude prediction in tokyo with artificial neural networks. *Neural Computing and Applications*, 28(5):1043–1055, 2017.

[18] K. Budiman and Y. N. Ifriza. Analysis of earthquake forecasting using random forest. *Journal of Soft Computing Exploration*, 2(2), 2021.

[19] J. Tezcan and Q. Cheng. Support vector regression for estimating earthquake response spectra. *Bulletin of Earthquake Engineering*, 10(4):1205–1219, 2012.

[20] J. Mahmoudi, M. A. Arjomand, M. Rezaei, and M. H. Mohammadi. Predicting the earthquake magnitude using the multilayer perceptron neural network with two hidden layers. *Civil Engineering Journal*, 2(1):1–12, 2016.

[21] J. Liu, C. Ji, J. Zhang, P. Zhang, L. Zeng, Z. Li, and W. Wang. Tectonic setting and general features of coseismic rupture of the 25 april, 2015 mw 7.8 gorkha, nepal earthquake. *Chinese Science Bulletin*, 60(27):2640–2658, 2015.

[22] R. K. Tiwari, H. Paudyal, and D. Shanker. On the spatio-temporal variation in b-value after 25 april 2015 gorkha, nepal earthquake. *Geodesy and Geodynamics*, 13(5):525–533, 2022.

[23] B. N. Upreti. An overview of the stratigraphy and tectonics of the nepal himalaya. *Journal of Asian Earth Sciences*, 17(5–6):577–606, 1999.

[24] G. C. Beroza, M. Segou, and S. Mostafa Mousavi. Machine learning and earthquake forecasting—next steps. *Nature Communications*, 12(1):10–12, 2021.

[25] S. M. Mousavi and G. C. Beroza. Machine learning in earthquake seismology. *Annual Review of Earth and Planetary Sciences*, 51:105–129, 2023.

[26] T. Chelidze, G. Melikadze, T. Kiria, T. Jimsheladze, and G. Kobzev. Statistical and nonlinear dynamics methods of earthquake forecast: Application in the caucasus. *Frontiers in Earth Science*, 8(June), 2020.

[27] A. Negarestani, S. Setayeshi, M. Ghannadi-Maragheh, and B. Akashe. Layered neural networks based analysis of radon concentration and environmental parameters in earthquake prediction. *Journal of Environmental Radioactivity*, 62(3):225–233, 2002.

[28] K. M. Asim, F. Martínez-Álvarez, A. Basit, and T. Iqbal. Earthquake magnitude prediction in hindukush region using machine learning techniques. *Natural Hazards*, 85(1):471–486, 2017.

[29] E. I. Alves. Earthquake forecasting using neural networks: Results and future work. *Nonlinear Dynamics*, 44(1-4):341–349, 2006.

[30] S. Sri Lakshmi and R. K. Tiwari. Model dissection from earthquake time series: A comparative analysis using modern non-linear forecasting and artificial neural network approaches. *Computers and Geosciences*, 35(2):191–204, 2009.

[31] R. Mallouhy, C. A. Jaoude, C. Guyeux, and A. Makhoul. Major earthquake event prediction using various machine learning algorithms. In *6th International Conference on Information and Communication Technologies for Disaster Management, ICT-DM 2019*, 2019.

[32] D. Di Giacomo, E. Robert Engdahl, and D. A. Storchak. The isc-gem earthquake catalogue (1904-2014): Status after the extension project. *Earth System Science Data*, 10(4):1877–1899, 2018.

[33] R. Jain, A. Nayyar, S. Arora, and A. Gupta. A comprehensive analysis and prediction of earthquake magnitude based on position and depth parameters using machine and deep learning models. *Multimedia Tools and Applications*, 80(18):28419–28438, 2021.

[34] C. N. Schuba, J. P. Schuba, G. G. Gray, and R. G. Davy. Interface-targeted seismic velocity estimation using machine learning. *Geophysical Journal International*, 218(1):45–56, 2019.

[35] T. Y. Hsu and A. Pratomo. Early peak ground acceleration prediction for on-site earthquake early warning using lstm neural network. *Frontiers in Earth Science*, 10(July):1–17, 2022.

[36] E. Harirchian and T. Lahmer. Improved rapid assessment of earthquake hazard safety of structures via artificial neural networks. In *IOP Conference Series: Materials Science and Engineering*, volume 897, 2020.

[37] B. Nadi, F. Askari, O. Farzaneh, S. Fatolahzadeh, and R. Mehdizadeh. Reliability evaluation of regression model for estimating coseismic landslide displacement. *Iranian Journal of Science and Technology - Transactions of Civil Engineering*, 44(1):165–173, 2020.