International Journal of Reconfigurable and Embedded Systems (IJRES)
Vol. 13, No. 3, November 2024, pp. 577~585
ISSN: 2089-4864, DOI: 10.11591/ijres.v13.i3.pp577-585

Earthquake magnitude prediction in Indonesia using a supervised method based on cloud radon data

Thomas Oka Pratama[1,2], Sunarno[2], Agus Budhie Wijatna[2], Eko Haryono[1,3]
[1]Doctoral Program in Environmental Science, Graduate School, Universitas Gadjah Mada, Yogyakarta, Indonesia
[2]Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Sleman, Indonesia
[3]Department of Environmental Geography, Faculty of Geography, Universitas Gadjah Mada, Sleman, Indonesia

Article Info

Article history:

Received Nov 2, 2023
Revised Jan 26, 2024
Accepted Mar 21, 2024

Keywords:

Cloud data
Earthquake magnitude
Machine learning
Radon
Supervised

ABSTRACT

In the challenging realm of earthquake prediction, the reliability of forecasting systems has remained a persistent obstacle. This study focuses on earthquake magnitude prediction in Indonesia, leveraging supervised machine learning techniques and cloud radon data. We present an analysis of the tele-monitoring system, data collection methods, and the application of regression-based machine learning algorithms. Utilizing a comprehensive dataset spanning 30 training instances and 105 test instances, the study evaluates multiple metrics to ascertain the efficacy of the prediction models. Our findings reveal that the linear regression approach yields the best earthquake magnitude prediction method, with the lowest values across multiple evaluation metrics: standard deviation 0.40, mean absolute error (MAE) 0.30, mean absolute percentage error (MAPE) 6%, root mean square error (RMSE) 0.52, mean squared error (MSE) 0.28, symmetric mean absolute percentage error (SMAPE) 0.06, and conformal normalized mean absolute percentage error (cnSMAPE) 0.97. Additionally, we discuss the implications of the research results and the potential applications in enhancing existing earthquake prediction methodologies.

Corresponding Author:

Sunarno
Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering
Universitas Gadjah Mada
Grafika Street No. 2, Sinduadi, Mlati, Sleman, Daerah Istimewa Yogykarta, Indonesia
Email: sunarno@ugm.ac.id

1. INTRODUCTION

Earthquake prediction has long been a formidable challenge, marked by the absence of a dependable forecasting system [1]. Various studies have attempted to anticipate seismic events through the analysis of diverse precursory indicators, including observations of animal behaviour, fluctuations in temperature, changes in radon gas emissions, and alterations in seismicity patterns [2], [3]. However, due to the inconsistent manifestation of these indicators preceding earthquakes, the standardization and generalization of these prediction methods have proven to be intricate [4]. Among these indicators, radon gas has garnered significant attention as a potential precursor to seismic activity [5]. Moreover, it underscores the replicable patterns associated with radon changes linked to seismic activity, particularly those identified in the lead-up to recent earthquakes [6]. While several studies have explored the use of radon gas concentration data in earthquake prediction, establishing an accurate forecasting system incorporating specific event details such as date, time, magnitude, and location has remained elusive [7]–[14].

The potential occurrence of an earthquake highlights the importance of precise prediction, which can potentially save lives and prevent damage to infrastructure. However, due to the inherent probabilistic nature of earthquakes and the difficulty in establishing an effective and reliable prediction model, attempts to forecast earthquakes have produced inconsistent outcomes [15]. Recent advancements in technology have led to the application of machine learning techniques in earthquake prediction, utilizing data related to animal behaviour, meteorological parameters, groundwater levels, chemical dynamics, seismic patterns, and historical earthquake data [14], [16]–[22]. Within the broader realm of machine learning, predictive modelling achieves enhanced accuracy by minimizing errors within the model [23]. Despite these efforts, accurate short-term earthquake predictions have remained elusive, specifically concerning the magnitude and location of seismic events on the Eurasian and Indo-Australian Plates [24].

Research by Zhang *et al.* [25], for instance, has focused on constructing four models using the extreme gradient boosting method to examine the mechanisms of radon variation under both natural and seismic conditions. The analysis highlighted the significant impact of various factors such as spring discharge, water temperature, precipitation, barometric pressure, and antecedent radon on radon anomalies, elucidating that these anomalies are likely induced by the earthquake-driven formation of microfractures in rock. Notably, the presence of ten megathrust subduction zones between the Eurasian and Indo-Australian Plates underscores the necessity for a robust earthquake magnitude prediction algorithm based on the fluctuation of radon gas concentration within one to four days before seismic events of magnitude above M4.5 [16].

However, despite these advancements, the correlation between earthquakes and radon anomalies has not been definitively established, leading to questions about the efficacy of proposed models [26]. Notably, the implementation of the belief rule-based expert system (BRBES) considering data about animal behaviour, environmental dynamics, and chemical changes has shown promising results in predicting earthquake occurrences within a 12-hour timeframe [17]. Similarly, research on the seismic cycle based on historical data, utilising an expert system, has exhibited accurate detection of impending earthquakes within 12 hours, with varying magnitudes (M3.6 to M9.1) and the location is separated into one-quarter of the earth [18]. Research by Tehseen *et al.* [24], the accuracy proposed expert system for making earthquake predictions using an independent test set has accuracy below 70% with magnitude range from M0.1–M5.9.

Moreover, the contemporary shift towards the integration of machine learning and deep learning methodologies in earthquake prediction has led to substantial advancements in the field approaches [24]. However, challenges persist, particularly concerning the accurate prediction of rare high-magnitude earthquakes and the inherent unpredictability of their timing and location [14]. This study aims to address these challenges by analysing an earthquake magnitude prediction algorithm that focuses on the fluctuation of radon gas concentration in the days leading up to seismic events of magnitude above M4.5 between the Eurasian and Indo-Australian Plates. Through the implementation of a supervised machine learning approach, this research endeavours to contribute to the existing body of knowledge on earthquake prediction methodologies.

2. METHOD

The radon gas concentration real-time telemonitoring system is measured close to an active fault in Yogyakarta, Indonesia, so it is vulnerable to seismic activity. The radon gas transducer is placed above ground level in the chamber room with a maximum distance of 4.142 cm to measure radon gas emissions effectively. Radon gas measurements change every 10 minutes to negate radiation emissions from Actinium and Thoron [27]. Figure 1 shows the earthquake prediction system design. Data from the transducer is then connected to the microprocessor and sent to the cloud server for real-time measurement data monitoring as long as you have internet access. Radon gas concentration measurement data is stored in a data storage server and displayed on a web server, while earthquake data comes from the Geofon Postdam and the Indonesian agency for meteorology, climatology, and geophysics.

Radon cloud data and earthquake data are then used to determine the earthquake magnitude prediction algorithm based on the supervised machine learning method. The results of this model are then evaluated based on mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), mean squared error (MSE), symmetric mean absolute percentage error (SMAPE), and conformal normalized mean absolute percentage error (cnSMAPE). The model with the best value can then be used in data processing on the cloud server to be processed into an earthquake prediction notification. Table 1 shows the radon data set composition based on the method by Pratama [16]. Data on radon gas concentrations and earthquake events were then tabulated in Table 2. The data used as training data and test data in machine learning are radon gas concentration data when there is an earthquake day prediction which comes from the method used by Pratama [16], and earthquake events 1-4 days after there is an earthquake day prediction with magnitude above M4.5 between Eurasia and Indo-Australia Plates. The beginning of data training was collected from the start from 15/9/2019 to 22/03/2020 (30 data), and then the data test started from 6/4/2020 until 31/12/2022 (105 data).

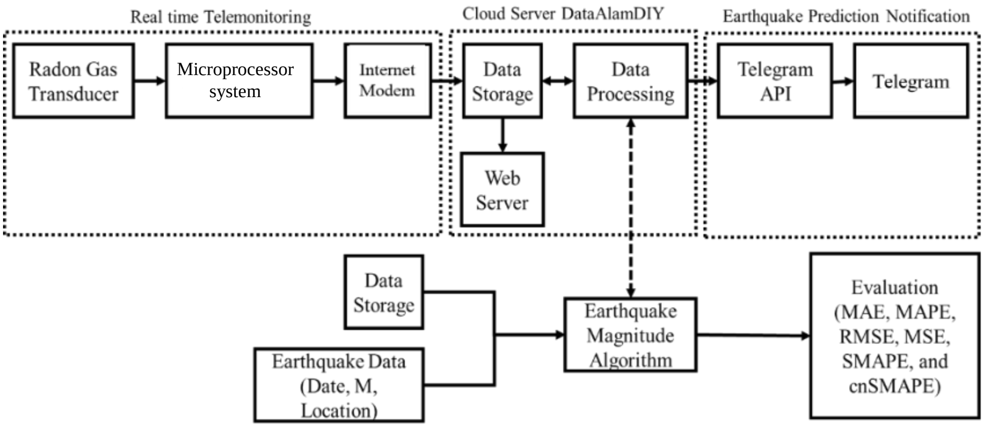

Figure 1. Earthquake prediction system design

Table 1. Data set composition [16]

Variable	Description
n	The day when the algorithm prediction was completed based on the method of Pratama [16]
Rn	Radon average day n
R(n-1)	Radon average day n-1
R(n-2)	Radon average day n-2
.	.
.	.
R(n-6)	Radon average day n-6
R(n-7)	Radon average day n-7
.	.
.	.
DR(n-3)	Radon average 3 days before R(n-2) = average R(n-3) until R(n-5)
DR(n-7)	Radon average 7 days before R(n-2) = average R(n-3) until R(n-9)
DR(n-14)	Radon average 14 days before R(n-2) = average R(n-3) until R(n-17)

Table 2. Example of dataset

Earthquake date prediction	DR (n-14)	DR (n-7)	DR (n-3)	R (n-7)	R (n-6)	R (n-5)	R (n-4)	R (n-3)	R (n-2)	R (n-1)	Earthquake date	Distance (km)	Actual magnitude
7-Nov-22	4.34	2.95	2.85	2.45	2.65	1.63	3.17	3.76	2.08	3.83	11-Nov-22	495.70	5.0
13-Nov-22	3.14	3.38	3.70	3.83	2.88	3.14	3.59	4.36	2.78	5.09	14-Nov-22	216.30	5.4
13-Nov-22	3.14	3.38	3.70	3.83	2.88	3.14	3.59	4.36	2.78	5.09	16-Nov-22	1124.37	5.6
18-Nov-22	9.62	16.32	32.81	2.78	5.09	20.33	23.05	55.04	15.19	41.97	21-Nov-22	380.36	5.6
29-Nov-22	18.29	2.93	3.35	2.59	1.16	1.20	5.36	3.50	3.11	1.83	3-Dec-22	311.97	6.1
4-Dec-22	8.27	3.45	3.46	3.11	1.83	4.27	2.60	3.51	2.47	2.00	6-Dec-22	462.60	6.2
5-Dec-22	6.12	3.04	2.86	1.83	4.27	2.60	3.51	2.47	2.00	3.40	8-Dec-22	378.19	5.8
9-Dec-22	2.93	2.93	3.32	2.47	2.00	3.40	4.06	2.50	2.14	3.90	13-Dec-22	584.16	5.2
13-Dec-22	4.35	5.88	9.68	2.50	2.14	3.90	15.78	9.37	3.85	2.44	17-Dec-22	611.76	5.1
14-Dec-22	4.41	5.94	9.67	2.14	3.90	15.78	9.37	3.85	2.44	2.50	18-Dec-22	903.52	5.1
16-Dec-22	4.32	5.71	2.93	15.78	9.37	3.85	2.44	2.50	2.30	2.40	19-Dec-22	706.85	5.3
23-Dec-22	4.40	3.09	4.26	1.79	2.37	3.23	4.32	5.24	3.07	1.89	25-Dec-22	210.73	5.3

The learning process in machine learning used in this study is supervised learning using a regression method shown in Figure 2. The goal is for the model to learn the underlying patterns or relationships in the data so that it can make precision earthquake magnitude predictions on new unseen data. Machine learning techniques used in this study to derive earthquake magnitude prediction algorithms are linear regression, tree, AdaBoost, Xtreme gradient boosting, and random forest [28]–[35]. The training data will be used to build the earthquake magnitude prediction model. Then the test data is used to test the earthquake magnitude prediction model that has been designed.

In this study, the linear regression, tree, AdaBoost, Xtreme gradient boosting, and random forest methods were performed using Orange Data Mining Version 3.35.0 software. Machine learning evaluation methods used include MAE, MAPE, RMSE, MSE, SMAPE, and cnSMAPE. By combining the implementation of machine learning models with evaluations using various metrics mentioned, this study can provide a more comprehensive understanding of the model's performance in predicting or analyzing the utilized data.

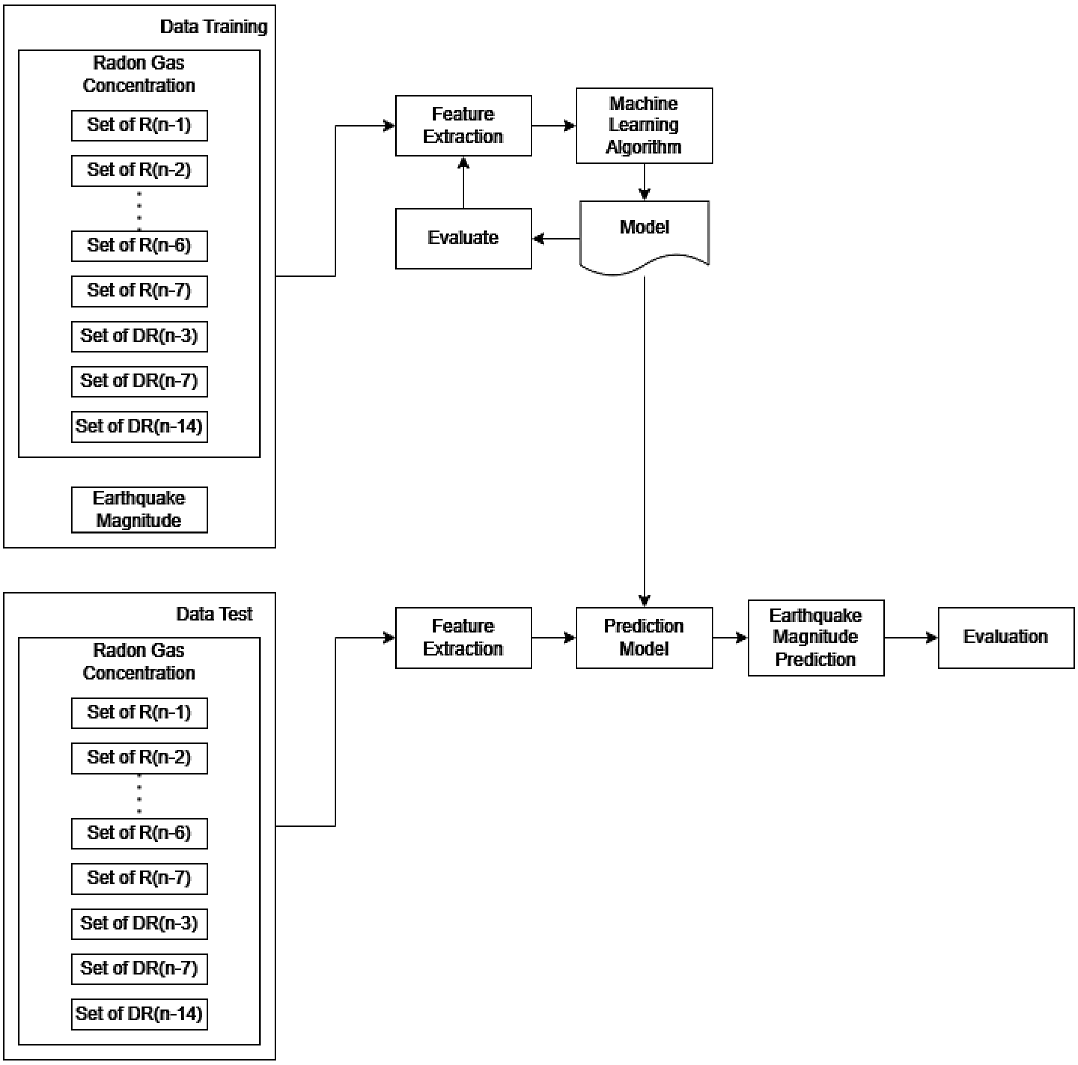

Figure 2. Scheme of a supervised machine learning model

3. RESULTS AND DISCUSSION

This study decided on earthquake magnitude prediction using a supervised machine learning method. Machine learning techniques used in this study to derive earthquake magnitude prediction algorithms are linear regression, tree, AdaBoost, Xtreme gradient boosting, and random forest. 30 training data were used in this supervised machine learning method and 105 test data. Setting features is done for each machine learning method to get the best results. The result obtained in this machine learning process is the prediction value of the magnitude of the earthquake that will occur based on the test data that has been entered. Earthquake predictions are valid for 1-4 days after the prediction based on the method used by Pratama *et al*. [7] which applies to locations between Aceh to East Nusa Tenggara, Indonesia.

Table 3 shows the recapitulation of prediction data using a supervised machine learning method based on a confusion matrix and standard deviation from the difference between actual magnitude and predicted magnitude. A true positive condition is stated when the actual magnitude is within the prediction range of magnitude ± Stdev error, while a false positive is when the actual magnitude is not within the prediction range of magnitude ± Stdev error. The precision value of the machine learning method is calculated by [32]:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (1)$$

The precision of earthquake prediction using the linear regression method has the highest value of 0.82, followed by AdaBoost with 0.80. The tree has the highest precision with a true positive conditions value of 86. The precision of Xtreme gradient boosting is 0.71 with the falsest positive, 30 conditions.

Table 3. Machine learning data test result

Parameter	Linear regression	Tree	AdaBoost	Xtreme gradient boosting	Random forest
Standard deviation	**0.52**	0.71	0.61	0.68	0.58
True positive	86	79	84	75	76
False positive	19	26	21	30	29
Precision	**0.82**	0.75	0.80	0.71	0.72

Some error evaluations of machine learning methods include relative error, MAE, MAPE, RMSE, MSE, SMAPE, and cnSMAPE. Table 4 shows the error evaluation of the earthquake magnitude prediction method using machine learning. The linear regression method has the lowest standard deviation (0.40), MAE (0.30), MAPE (6%), RMSE (0.52), MSE (0.28), SMAPE (0.06) and cnSMAPE (0.97) values compared to other machine learning methods. Lower values for these metrics indicate better performance of the algorithm. Therefore, since linear regression has the lowest values for all these metrics, it is considered the best method for predicting earthquake magnitude based on the steps used in this research. Based on the prediction results of the earthquake using the recapitulated data set, the Tree method has the lowest evaluation result value with the highest standard deviation (0.48), MAE (0.50), MAPE (10%), RMSE (0.71), MSE (0.50), SMAPE (0.09) and the lowest cnSMAPE (0.95). With these values and compared to other machine learning methods, the tree method is the worst method for predicting earthquakes based on the data set determined in this study. To show the error characteristics, Figure 3 shows the dispersion errors using boxplot representation for each method. The tree method has the highest error dispersion, followed by Xtreme gradient boosting, random forest, AdaBoost, and linear regression which has the lowest error dispersion so that it can be stated as the best method in predicting earthquake magnitude using the data set.

Table 4. Earthquake magnitude prediction error evaluation

Error index	St dev of absolute error	MAE (s)	MAPE (%)	RMSE	MSE	SMAPE	cnSMAPE
Linear regression	**0.40**	**0.30**	**6%**	**0.52**	**0.28**	**0.06**	**0.97**
Tree	0.48	0.50	10%	0.71	0.50	0.09	0.95
AdaBoost	0.46	0.40	7%	0.61	0.38	0.08	0.96
Xtreme gradient boosting	0.46	0.50	9%	0.67	0.45	0.09	0.95
Random forest	0.40	0.40	8%	0.58	0.34	0.08	0.96

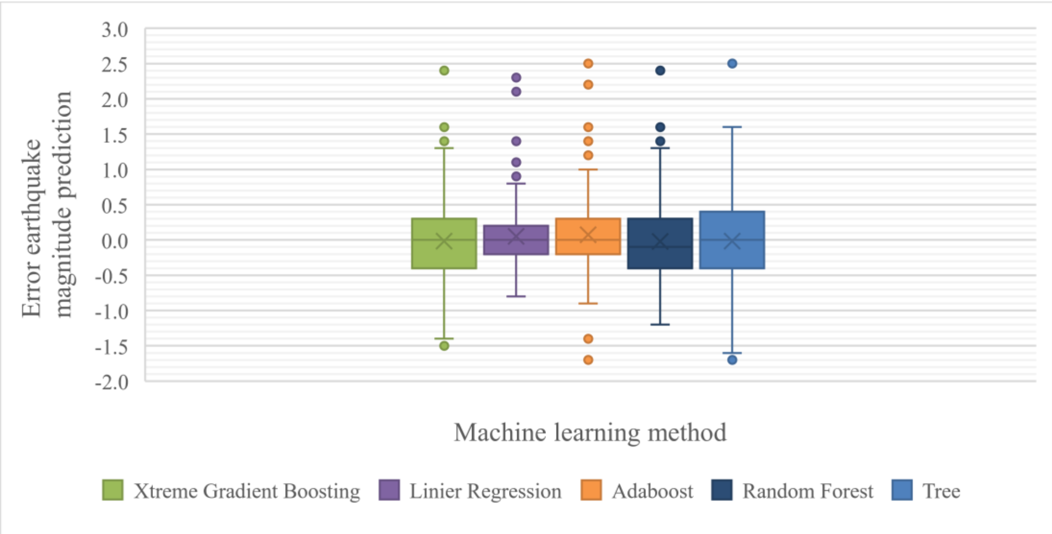

Figure 3. Boxplot produced by machine learning algorithms when predicting the 105 data test

To analyze in detail the sign of deviation produced by the methods in predicting earthquake magnitude, Figure 4 shows the histogram of errors for machine learning method Xtreme gradient boosting (Figure 4(a)), linear regression (Figure 4(b)), AdaBoost (Figure 4(c)), random forest (Figure 4(d)), and tree (Figure 4(e)). The Xtreme gradient boosting, linear regression and AdaBoost methods have the highest frequency of values at 0 M error, while the random forest and tree methods are at -0.5 M and -0.25 M respectively. Linear regression has the highest error frequency with a quantity of 33 at 0 M followed by -0.25 M and -0.5 M errors with a quantity of 26 and 19 states. This also indicates that the linear regression method is the best in predicting earthquake magnitude based on the test data in this study.

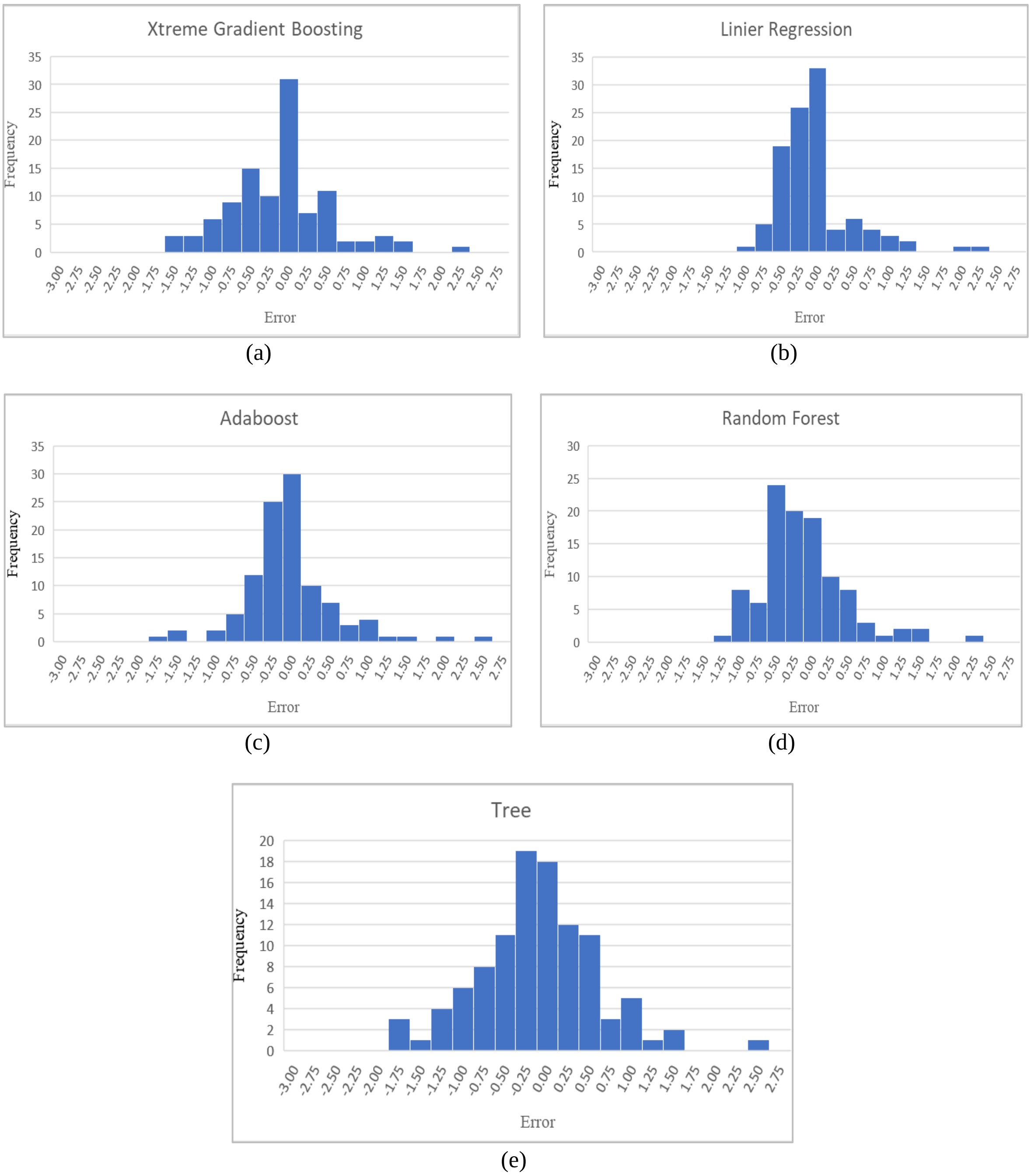

Figure 4. Histograms of the errors produced by (a) Xtreme gradient boosting, (b) linear regression, (c) AdaBoost, (d) random forest, and (e) tree algorithms when predicting the 105 data test

In this study, the errors for the magnitude range were also analyzed, as can be seen in Table 5, which shows that the linear regression method has the lowest MAE for the M5.1-M5.3 earthquake magnitude range, with a value of 0.08, for M4.8-M5.1 and M5.3-M5.6 being 0.28 and 0.22, respectively. The absolute error standard deviation of the linear regression method also has low values for most magnitude ranges with the lowest value being 0.08 in the M5.1-M5.3 magnitude range. The Xtreme gradient boosting method has the lowest absolute error standard deviation value for the magnitude range M5.7-M5.9 and over M6.5 with values of 0.12 and 0.43, respectively. In the actual magnitude range M5.1-M5.3, the AdaBoost method has a MAE of 0.22 which is lower than the MAE of the random forest method with a value of 0.24. In this analysis, the AdaBoost method has a MAE for magnitudes M4.8-M5.1 and M5.3-M5.6 of 0.29. Earthquakes with magnitudes greater than M6.2 are rare, and earthquakes cannot be engineered by humans. More data will make the system learn more so that it can predict earthquake magnitudes more precisely and accurately.

Table 5. Evaluation of the absolute errors based on the actual magnitude range produced by machine learning algorithms when predicting the 105 data test

	Absolute error mean					Absolute error standard deviation				
Actual magnitude range (m)	Xtreme gradient boosting	Linear regression	AdaBoost	Random forest	Tree	Xtreme gradient boosting	Linear regression	AdaBoost	Random forest	Tree
4.5-4.7	0.58	0.62	0.62	0.54	0.60	0.24	**0.11**	**0.11**	0.25	0.19
4.8-5	0.38	**0.28**	**0.29**	0.37	0.32	0.42	**0.11**	0.40	0.31	0.46
5.1-5.3	0.34	**0.08**	**0.22**	**0.24**	0.46	0.36	**0.08**	0.25	0.22	0.45
5.4-5.6	0.40	**0.22**	**0.29**	0.32	0.41	0.29	**0.13**	0.18	0.20	0.27
5.7-5.9	0.70	0.64	0.54	0.58	0.66	**0.12**	0.17	0.32	0.19	0.26
6-6.2	0.88	0.90	0.96	0.82	0.98	0.88	**0.10**	0.18	0.28	0.19
6.3-6.5	1.40	1.10	1.20	1.40	1.50	-	-	-	-	-
>6.5	1.78	1.80	1.93	1.70	1.63	**0.43**	0.47	0.51	0.48	0.63

4. CONCLUSION

The results demonstrated the effectiveness of the linear regression method in predicting earthquake magnitudes, with the lowest values across multiple evaluation metrics: standard deviation (0.40), MAE (0.30), MAPE (6%), RMSE (0.52), MSE (0.28), SMAPE (0.06) and cnSMAPE (0.97). With these results, the linear regression method model will be implemented in the server cloud of the earthquake early warning system that has been created. These findings underscore the potential of our approach to improve real-world disaster preparedness and mitigation efforts. The challenges remain in predicting rare high-magnitude earthquakes, the study provides a significant advancement in the field. Future research directions may involve incorporating more data to improve the precision of earthquake magnitude predictions, further contributing to the body of knowledge on this critical area of research.

ACKNOWLEDGEMENTS

The author thanks to Sensor System dan Tele-Control Laboratory research team at the Department of Nuclear Engineering and Engineering Physics, Universitas Gadjah Mada, Indonesia, provided the radon gas telemonitoring system. We thank Postdam Geofon and *Badan Meteorologi, Klimatologi dan Geofisika* Indonesia, for providing the earthquake data. We kindly acknowledge the support of Director of Research, Technology and Community Service, Directorate General of Higher Education, Research and Technology, Ministry of Education, Culture, Research and Technology, Indonesia as a funder with contract number 0536/E5/PG.02.00/2023.

REFERENCES

[1] M. Senthilkumar, D. Gnanasundar, B. Mohapatra, A. K. Jain, A. Nagar, and P. K. Parchure, “Earthquake prediction from high frequency groundwater level data: A case study from Gujarat, India,” *HydroResearch*, vol. 3, pp. 118–123, 2020, doi: 10.1016/j.hydres.2020.10.004.

[2] B. Bahrami and M. Shafiee, “Fuzzy descriptor models for earthquake time prediction using seismic time series,” *International Journal of Uncertainty, Fuzziness and Knowldege-Based Systems*, vol. 23, no. 4, pp. 505–519, 2015, doi: 10.1142/S0218488515500221.

[3] A. Ahumada, A. Altunkaynak, and A. Ayoub, “Fuzzy logic-based attenuation relationships of strong motion earthquake records,” *Expert Systems with Applications*, vol. 42, no. 3, pp. 1287–1297, Feb. 2015, doi: 10.1016/j.eswa.2014.09.035.

[4] S. F. G. Aboonasr, A. Zamani, F. Razavipour, and R. Boostani, “Earthquake hazard assessment in the Zagros Orogenic Belt of Iran using a fuzzy rule-based model,” *Acta Geophysica*, vol. 65, no. 4, pp. 589–605, Aug. 2017, doi: 10.1007/s11600-017-0055-4.

[5] C. H. Scholz, L. R. Sykes, and Y. P. Aggarwal, “Earthquake prediction: a physical basis,” *Science*, vol. 181, no. 4102, pp. 803–810, Aug. 1973, doi: 10.1126/science.181.4102.803.

[6] Y. Omori, H. Nagahama, Y. Yasuoka, and J. Muto, "Radon degassing triggered by tidal loading before an earthquake," *Scientific Reports*, vol. 11, no. 1, 2021, doi: 10.1038/s41598-021-83499-0.

[7] T. O. Pratama, Sunarno, S. Hawibowo, M. M. Waruwu, and R. Wijaya, "Deterministic system for earthquake early warning system based on radon gas concentration anomaly at yogyakarta region-Indonesia," in *AIP Conference Proceedings*, 2021, p. 040003. doi: 10.1063/5.0037683.

[8] Sunarno, H. L. Firdaus, Y. F. Luckyarno, M. M. Waruwu, and R. Wijaya, "Detection system for deterministic earthquake prediction based on radon concentration changes in Indonesia," *Journal of Engineering Science and Technology*, vol. 15, no. 3, pp. 1787–1798, 2020.

[9] Sunarno, M. M. Waruwu, and R. Wijaya, "Development of the real time telemonitoring system for earthquake prediction deduced from fluctuations in groundwater levels at Yogyakarta region-Indonesia," *Journal of Theoretical and Applied Information Technology*, vol. 83, no. 1, pp. 95–99, 2016.

[10] R. Gas, "EPSC 330 presentation earthquake precursors: radon gas," *Sappho.Eps.Mcgill.Ca*, Accessed: Oct. 02, 2024. [Online]. Available: http://sappho.eps.mcgill.ca/~olivia/EES/Presentations/Presentations-2018/Emily-Dazee_PresentationSummary.pdf

[11] A. S. Bafti, "The relation of Concentration radon gas in underground water with tectonic movements and Seismicity. Case Study: Jorjafk fault, Central Iran," *Journal of Geoscience*, vol. 30, no. 117, pp. 189–204, 2020, doi: 10.22071/gsj.2018.91418.1186.

[12] L. Cao and A. Gao, "Correlativity between short-term change of fault gas radon concentration and air temperature & atmospheric pressure," *Acta Seismologica Sinica*, no. 4, pp. 719–729, 2014, doi: 10.3969/j.issn.0253-3782.2014.04.017.

[13] C. C. Fu *et al.*, "Preseismic anomalies in soil-gas radon associated with 2016 M6.6 Meinong earthquake, Southern Taiwan," *Terrestrial, Atmospheric and Oceanic Sciences*, vol. 28, no. 5, pp. 787–798, 2017, doi: 10.3319/TAO.2017.03.22.01.

[14] M. H. Al Banna *et al.*, "Application of artificial intelligence in predicting earthquakes: state-of-the-art and future challenges," *IEEE Access*, vol. 8, pp. 192880–192923, 2020, doi: 10.1109/ACCESS.2020.3029859.

[15] E. Abebe, H. Kebede, M. Kevin, and Z. Demissie, "Earthquakes magnitude prediction using deep learning for the Horn of Africa," *Soil Dynamics and Earthquake Engineering*, vol. 170, p. 107913, Jul. 2023, doi: 10.1016/j.soildyn.2023.107913.

[16] T. O. Pratama, "Earthquake early warning system based on radon gas concentration and groundwater level fluctuation at Yogyakarta Region-Indonesia," Thesis, Master of Engineering Physics, Universitas Gadjah Mada, Yogyakarta-Indonesia, 2021. [Online]. Available: http://etd.repository.ugm.ac.id/penelitian/detail/196902

[17] M. S. Hossain, A. Al Hasan, S. Guha, and K. Andersson, "A belief rule based expert system to predict earthquake under uncertainty," *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, vol. 9, no. 2, pp. 26–41, 2018, doi: 10.22667/JOWUA.2018.06.30.026.

[18] A. Ikram and U. Qamar, "Developing an expert system based on association rules and predicate logic for earthquake prediction," *Knowledge-Based Systems*, vol. 75, pp. 87–103, Feb. 2015, doi: 10.1016/j.knosys.2014.11.024.

[19] P. Hajikhodaverdikhan, M. Nazari, M. Mohsenizadeh, S. Shamshirband, and K. W. Chau, "Earthquake prediction with meteorological data by particle filter-based support vector regression," *Engineering Applications of Computational Fluid Mechanics*, vol. 12, no. 1, pp. 679–688, Jan. 2018, doi: 10.1080/19942060.2018.1512010.

[20] 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, Jan. 2017, doi: 10.1007/s11069-016-2579-3.

[21] G. Asencio-Cortés, A. Morales-Esteban, X. Shang, and F. Martínez-Álvarez, "Earthquake prediction in California using regression algorithms and cloud-based big data infrastructure," *Computers and Geosciences*, vol. 115, pp. 198–210, Jun. 2018, doi: 10.1016/j.cageo.2017.10.011.

[22] T. Khan, M. Rabbani, S. M. T. Siddiquee, and A. Majumder, "An innovative data mining approach for determine earthquake probability based on linear regression algorithm," in *Proceedings of 2019 3rd IEEE International Conference on Electrical, Computer and Communication Technologies, ICECCT 2019*, IEEE, Feb. 2019, pp. 1–4. doi: 10.1109/ICECCT.2019.8869286.

[23] H. Alaskar and T. Saba, "Machine learning and deep learning: a comparative review," *Proceedings of Integrated Intelligence Enable Networks and Computing IIENC 2020*, 2021, pp. 143–150. doi: 10.1007/978-981-33-6307-6_15.

[24] R. Tehseen, M. S. Farooq, and A. Abid, "Earthquake prediction using expert systems: a systematic mapping study," *Sustainability (Switzerland)*, vol. 12, no. 6, pp. 1–32, Mar. 2020, doi: 10.3390/su12062420.

[25] S. Zhang, Z. Shi, G. Wang, R. Yan, and Z. Zhang, "Application of the extreme gradient boosting method to quantitatively analyze the mechanism of radon anomalous change in Banglazhang hot spring before the Lijiang Mw 7.0 earthquake," *Journal of Hydrology*, vol. 612, p. 128249, Sep. 2022, doi: 10.1016/j.jhydrol.2022.128249.

[26] V. Walia, H. S. Virk, T. F. Yang, S. Mahajan, M. Walia, and B. S. Bajwa, "Earthquake prediction studies using radon as a precursor in N-W Himalayas, India: A case study," *Terrestrial, Atmospheric and Oceanic Sciences*, vol. 16, no. 4, pp. 775–804, 2005, doi: 10.3319/TAO.2005.16.4.775(GIG).

[27] H. Cember and T. E. Johnson, *Introduction to health physics*, 4th ed. New York: McGraw-Hill Medical, 2009.

[28] M. Micucci and A. Iula, "Recent advances in machine learning applied to ultrasound imaging," *Electronics (Switzerland)*, vol. 11, no. 11, pp. 1–30, Jun. 2022, doi: 10.3390/electronics11111800.

[29] E. Ismanto and M. Novalia, "Performance comparison of C4.5 algorithms, random forest, and gradient boosting for commodity classification (in Indonesia: *Komparasi kinerja algoritma C4.5, random forest, dan gradient boosting untuk klasifikasi komoditas*)," *Techno.Com*, vol. 20, no. 3, pp. 400–410, Aug. 2021, doi: 10.33633/tc.v20i3.4576.

[30] T. Zhang and B. Li, "Loan prediction model based on AdaBoost and PSO-SVM," in *Proceedings of the 2018 International Conference on Network, Communication, Computer Engineering (NCCE 2018)*, Paris, France: Atlantis Press, 2018. doi: 10.2991/ncce-18.2018.120.

[31] C. Tu, H. Liu, and B. Xu, "AdaBoost typical algorithm and its application research," *MATEC Web of Conferences*, vol. 139, p. 00222, Dec. 2017, doi: 10.1051/matecconf/201713900222.

[32] A. Arista, "Comparison decision tree and logistic regression machine learning classification algorithms to determine COVID-19," *Sinkron*, vol. 7, no. 1, pp. 59–65, Jan. 2022, doi: 10.33395/sinkron.v7i1.11243.

[33] Y. Hou, "Decision tree algorithm for big data analysis," *Advances in Intelligent Systems Research*, vol. 161, pp. 1–5, 2018, doi: 10.2991/tlicsc-18.2018.43.

[34] B. Charbuty and A. Abdulazeez, "Classification based on decision tree algorithm for machine learning," *Journal of Applied Science and Technology Trends*, vol. 2, no. 1, pp. 20–28, Mar. 2021, doi: 10.38094/jastt20165.

[35] Y. Zhang and A. Haghani, "A gradient boosting method to improve travel time prediction," *Transportation Research Part C: Emerging Technologies*, vol. 58, pp. 308–324, Sep. 2015, doi: 10.1016/j.trc.2015.02.019.

BIOGRAPHIES OF AUTHORS

Thomas Oka Pratama, S.T., M.Eng. holds a doctor of environmental science from Universitas Gadjah Mada in 2021. He also received his S.T. and M.Eng. (engineering physics) from Universitas Gadjah Mada in 2014 and 2021, respectively. He is currently a lecturer in the engineering physics program, in the Department of Nuclear Engineering and Engineering Physics at Universitas Gadjah Mada, Indonesia. His research includes a telemonitoring system, and earthquake prediction based on the radon gas concentration and groundwater level. He can be contacted at email: thomas.o.p@ugm.ac.id.

Prof. Ir. Sunarno, M.Eng., Ph.D., IPU specializes in the fields of engineering, instrumentation and control, and engineering physics. He is actively involved in the engineering physics, nuclear engineering, and instrumentation cluster within the realm of science and technology. His research interests revolve around instrumentation for telemetry and telecontrol, as well as early warning systems for natural disasters. In terms of community services, he has conducted several training programs. He can be contacted at email: sunarno@ugm.ac.id.

Prof. Dr. Ir. Agus Budhie Wijatna, M.Si., IPM. focuses his research on the application of hydroisotope tracing in the environmental and radiation fields. His notable research works include "*Sistem informasi geografis untuk pemetaan konsentrasi radon tanah di Daerah Istimewa Yogyakarta sebagai referensi dalam analisis kebijakan kesehatan masyarakat*" [2021] and "*Rancang Bangun Sistem Pemantau Ultraviolet Untuk Peringatan Dini Bahaya Perubahan Cuaca Ekstrim*" [2018]. He has also been involved in the creation of intellectual property, notably the method of verifying topographic, geological, and hydrogeological approaches using the Hydroisotope method to determine groundwater recharge areas [2023]. Moreover, his significant publications include "determination of groundwater recharge area by using hydroisotope technic of sei bingei area and surrounding areas, Langkat Regency, North Sumatra" [2020], "Tracing the origin of springs water by environmental isotope in the southern slope of Mount Merapi, Indonesia" [2013], "*Studi variabilitas isotop airhujan sebagai fungsi elevasi untuk mendapatkan merapi meteoric water line* (MMWL)" [2013], and "*Studi konektivitas akuifer antara sumur bor dengan sumberdaya air di bawahnya*" [2013]. He can be contacted at email: budiwijatna@ugm.ac.id.

Prof. Dr. Eko Haryono, M.Si. is a seasoned expert in physical geography and environmental science, particularly in the field of karst geomorphology, karst hydrogeology, and landscape ecology. With a comprehensive educational background, including a Ph.D. in Geography from Universitas Gadjah Mada, Indonesia, with a thesis on the Karst development model in Karangbolong, Gunungsewu, Blambangan, and Rengel, he has dedicated over fifteen years to researching various aspects of karst landscapes. He has also played significant roles as the head of the Department of Environmental Geography and the head of the Doctoral Program in Environmental Science at Universitas Gadjah Mada. His extensive contributions to the field are evident through his involvement in various professional associations, such as the Karst Commission Steering Committee at the International Geographical Union and the Karst Commission of the International Association of Hydrogeologists. Additionally, he has led several research projects, including "*Karakterisasi nilai penting kawasan karst sangkulirang-mankalihat, kalimantan timur*" funded by USAID-Yayasan KEHATI and "reconstruction sea level change in Indonesia, evidence from Karstic Island of Maratua,". He can be contacted at email: e.haryono@ugm.ac.id.