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Earthquake magnitude prediction based on radon cloud data near Grindulu fault, Indonesia using the statistical method

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ABSTRACT

Earthquake prediction is one of the most challenging and vital tasks that demands new methodologies for improving the accuracy of predictions. The research aims to present how radon gas concentration fluctuations are associated with the prediction of earthquakes in the Eurasian-Indo-Australian Plates. The paper discusses a statistical method of forecasting earthquake magnitudes greater than M4.5 from real-time radon gas monitoring close to the Grindulu Fault, Pacitan, East Java, Indonesia. This developed model has had the least errors in the form of mean absolute error (MAE), 0.30; mean absolute percentage error (MAPE), 0.06; root mean square error (RMSE), 0.55; mean squared error (MSE), 0.30; symmetric mean absolute percentage error (SMAPE), 0.06; complex normalized mean absolute percentage error (cnMAPE), 0.97; error absolute average (EAA), 0.30; and error relative average (ERA), -0.11, showing great accuracy and uniformity in prediction. These observations support the model's efficiency that may be adopted in earthquake early warning systems for better disaster preparedness. Predictive errors are reduced, and there is support for improved disaster management strategy, public safety education, and effective emergency response personnel training. This study can be used as a foothold for further advances in earthquake prediction methodologies and refinement of early warning systems.

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1. INTRODUCTION

Earthquakes, as one of the most devastating natural disasters, strike suddenly, inflicting widespread damage to structures and tragically claiming lives [1], [2]. Numerous research efforts have explored the potential for earthquake prediction through the examination of various precursory signals, including animal behaviour, temperature fluctuations, radon gas emissions, seismic activity alterations, and related indicators [3], [4]. However, due to the inconsistent presence of these precursory indicators before each seismic event, the standardization of forecasting approaches remains a significant challenge [5]. Inaccurate forecasts in many existing methods contribute to the devastating consequences of earthquakes [2]. Radon gas has long been considered a potential early indicator of earthquakes [6]–[12]. Yet a comprehensive prediction system specifying the date, time, magnitude, and precise location of impending earthquakes remains [2], [9]–[12].

Recently, artificial intelligence (AI)-driven approaches have shown promising advancements in earthquake prediction, surpassing traditional methods in accuracy. These techniques leverage machine learning to analyze diverse data sources, including animal behaviour, weather patterns, groundwater levels, chemical changes, and seismic activity, enabling the identification of potential warning signs before earthquakes occur. AI-based methodologies are currently helpful for earthquake prediction, emphasizing its potential to improve preparedness and response strategies in at-risk areas [2], [13]–[18]. While short-term earthquake prediction with specific magnitude and location remains a challenge, this study presents a unique approach for predicting earthquakes with a magnitude above M4.5 in Indonesia between the Eurasian and Indo-Australian Plates [19].

Zhang's study constructs four models to analyse the mechanisms of radon variation under natural and seismic conditions using the extreme gradient boosting method. Analysis of the precursory mechanisms of these radon anomalies found that radon anomalies are most likely caused by increases in radon emanation due to the earthquake-induced formation of microfractures in rock [20]. Related works in the field of earthquake prediction reveal diverse approaches and methodologies, each with its unique set of challenges and potential. Walia's assessment highlights the absence of a definitive model linking earthquakes and radon anomalies, underscoring the ongoing need for further validation of proposed models [21]. On the other hand, the application of belief rule-based expert system (BRBES) demonstrates the potential to anticipate earthquake occurrences within a maximum of 12 hours, drawing upon data on animal behaviour, environmental shifts, and chemical variations [13]. Contradicting the conventional four-stage prediction framework, research on the Haicheng earthquake indicates that the observed rise in seismic activity preceding the event does not align with the anticipated prediction stages [22]. Examining the seismic cycle based on historical data, an expert system showcased the capability to detect 100% of earthquakes within 12 hours within specific parameters of range, depth, and location, estimating magnitudes ranging from M3.6 to M9.1 across one-quarter of the Earth's surface [14]. Leveraging climate data, Hajikhodaverdikhan *et al.* [15] successfully predicts earthquakes near Tabriz, Iran, boasting high accuracy and precision rates in monthly earthquake forecasts.

In the realm of earthquake prediction methodologies, machine learning and deep learning have emerged as focal points, as evidenced by the application of various techniques such as pattern recognition neural networks, recurrent neural networks, random forests, and linear programming boost ensemble classifiers. These techniques have been separately employed to model the relationships between calculated seismic parameters and forthcoming earthquakes with magnitudes greater than or equal to 5.5 within a one-month prediction timeframe, though significant challenges persist in the integration of these models into effective forecasting systems [16]. With the aid of the support vector regression method, climate data is utilized to predict earthquake magnitudes in specific regions, achieving a precision rate of 96% for mean magnitude forecasts and a high accuracy rate of 78% in projected monthly earthquake counts [15]. Conversely, the application of linear regression in earthquake prediction through data mining, considering groundwater levels, chemical changes, and radon gas in groundwater, has faced challenges in understanding the intricate interplay of these factors without rigorous empirical investigation [18].

Reflecting on the utility of AI in earthquake prediction, Banna's discussion emphasizes the effective forecasting of earthquakes within specific magnitude ranges (M3 to M5), with limitations observed in predicting high-magnitude events due to their relative rarity and unpredictable occurrence patterns. Notably, significant errors in time and location prediction have been encountered, with deviations of up to 70 miles and substantial variation in prediction time frames ranging from 20 days to 5 months [2]. Based on Tehseen *et al.*'s study [19], the accuracy proposed expert system for making earthquake predictions using an independent test set is shown in Table 1.

Table 1. Accuracy is claimed in an expert system using an independent test set [19]

References	Number of earthquake records	Accuracy (%)	Magnitude range
[23]	9531	69.8	≥2.0
[24]	12690	50.14	≥3.0
[25]	337	63	≥3.0
[26]	10567	40	0.1–5.9

These findings underscore the complexity and inherent uncertainties associated with earthquake prediction, driving the ongoing exploration and refinement of methodologies to enhance predictive accuracy and reliability. The research trend has shifted towards machine learning and deep learning methodologies since 2018, marking a significant transition in earthquake prediction techniques [19]. Previous research has focused on radon gas concentration fluctuations one to four days before an earthquake event based on Thomas Oka's earthquake date prediction method between the Eurasia and Indo-Australia plates in Indonesia [27]. The latest research on predicting earthquake magnitudes using a linear regression technique has achieved the lowest values across various evaluation metrics based on the radon gas fluctuation in Yogyakarta, Indonesia. The results include a standard deviation of 0.40, mean absolute error (MAE) of 0.30, mean absolute percentage error (MAPE) of 6%, root mean square error (RMSE) of 0.52, mean squared error (MSE) of 0.28, symmetric mean absolute percentage error (SMAPE) of 0.06, and cnSMAPE of 0.97.

There have been one to four days of earthquake date prediction before the event based on radon gas concentration measurements near the Grindulu Fault in Pacitan, East Java, Indonesia. Still, the magnitude is not yet predicted [27]. This research seeks magnitude prediction through radon gas concentration fluctuations in the Eurasian and Indo-Australian Plates, focusing on earthquakes with magnitudes greater than M4.5, and then implementing an earthquake early warning system based on the radon gas concentration. This study discusses using the statistical method for magnitude prediction to improve the earthquake early warning system, to reduce the risk of being affected by disasters, and to prepare emergency response actions.

2. METHOD

The radon gas telemonitoring system is installed near the active Grindulu fault in Pacitan, East Java, Indonesia, in such a way that the system becomes most sensitive to earthquakes. The radon gas sensor is exactly put in a controlled chamber for optimally achieving accurate data, which is approximately around the fault area. The frequency of radon gas measurements is adjusted every 10 minutes to minimize the impact of radiation emissions from Actinium and Thoron [28]. Figure 1 illustrates the overall architecture of the monitoring system. The sensor readings are logged and sent continuously to an ESP32 microprocessor and then to a cloud server, enabling real-time monitoring provided by an internet connection. The readings of the concentration of the radon gas are logged securely to a dedicated storage server, from which the users can retrieve them using a cloud-based interface. Besides, earthquake data analysis relies on safely stored radon measurements and earthquake occurrence records to allow reliable monitoring and prediction capabilities.

The earthquake magnitude prediction algorithm is developed using statistical methods, employing data from Radon clouds and earthquake occurrences. Performance evaluation of the model includes metrics such as MAE, MAPE, RMSE, MSE, SMAPE, and cnSMAPE. The optimal model is selected for deployment on a cloud server for earthquake prediction notifications.

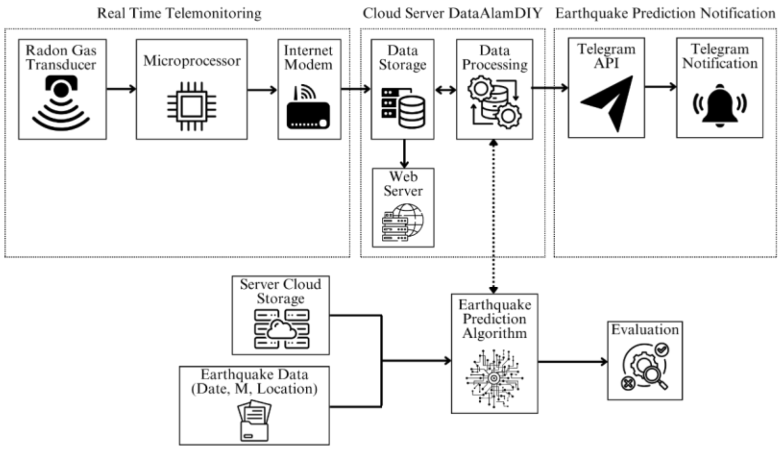

Figure 1. Earthquake magnitude prediction scheme [29]

Table 2 presents the dataset structure for radon gas concentration, arranged based on the methodology developed by Pratama *et al*. [27]. Subsequently, detailed information regarding radon gas concentration and earthquake activities was structured and tabulated systematically in Table 3 following Thomas Oka's framework. The training dataset consists of radon gas concentration data recorded during the prediction interval of earthquake activities. Data were collected from 156 cases in the study area, of which 80% were utilized as training data and 20% for predicting and testing earthquake magnitudes. Data structure and distribution align closely with the method already established, which is standard and reliable for outcomes.

The algorithm for earthquake magnitude prediction is determined through stages starting from data tabulation and synchronization until the performance evaluation values are obtained. The algorithm for each station is determined by the flowchart shown in Figure 2. Subsequently, the data is computed to determine the *a* value. A selection occurs when an earthquake date prediction is made using the existing algorithm. Various combinations of *a* are tested to derive *b*, the characteristic coefficient. The next step is to establish the relationship between *b* and *c*, where *c* represents the earthquake magnitude recorded by the earthquake precursor telemonitoring station. This process results in a polynomial formula that defines the relationship between *b* and *c*. The earthquake magnitude can be predicted by substituting *b* into this polynomial formula. Following this, the performance evaluation of the predicted earthquake magnitudes is calculated. The evaluation of the machine learning process encompassed metrics such as MAE, MAPE, RMSE, MSE, SMAPE, and cnSMAPE.

Table 2. Data set composition [27]

Variable	Description
x	The day when the algorithm prediction was completed based on the method of Thomas Oka for Pacitan station [27].
Rx	Radon average day *x*
R(x-1)	Radon average day *x-1*
R(x-2)	Radon average day *x-2*
R(x-6)	Radon average day *x-6*
R(x-7)	Radon average day *x-7*
HR(x-3)	Radon average 3 days before *R(x-2)* = average *R(x-3)* to *R(x-5)*
HR(x-7)	Radon average 7 days before *R(x-2)* = average *R(x-3)* to *R(x-9)*
HR(x-14)	Radon average 14 days before *R(x-2)* = average *R(x-3)* to *R(x-17)*

Table 3. Example of dataset

Earthquake date prediction	HR (*x-14*)	HR (*x-7*)	HR (*x-3*)	R (*x-7*)	R (*x-6*)	R (*x-5*)	R (*x-4*)	R (*x-3*)	R (*x-2*)	R (*x-1*)	Earthquake date	Real magnitude
12/2/2023	87.17	91.50	102.86	83.23	74.81	91.70	105.12	111.76	104.13	122.15	12/3/2023	4.7
12/7/2023	100.48	115.76	122.38	104.13	122.15	143.17	118.75	105.22	118.59	86.00	12/11/2023	4.9
12/18/2023	99.86	92.67	104.19	92.32	83.15	102.89	103.07	106.59	101.28	51.95	12/22/2023	4.8
12/25/2023	81.82	70.96	77.29	52.73	58.91	83.57	71.01	77.29	64.34	75.01	12/26/2023	4.6
12/26/2023	81.34	65.69	70.88	58.91	83.57	71.01	77.29	64.34	75.01	69.46	12/28/2023	5.1

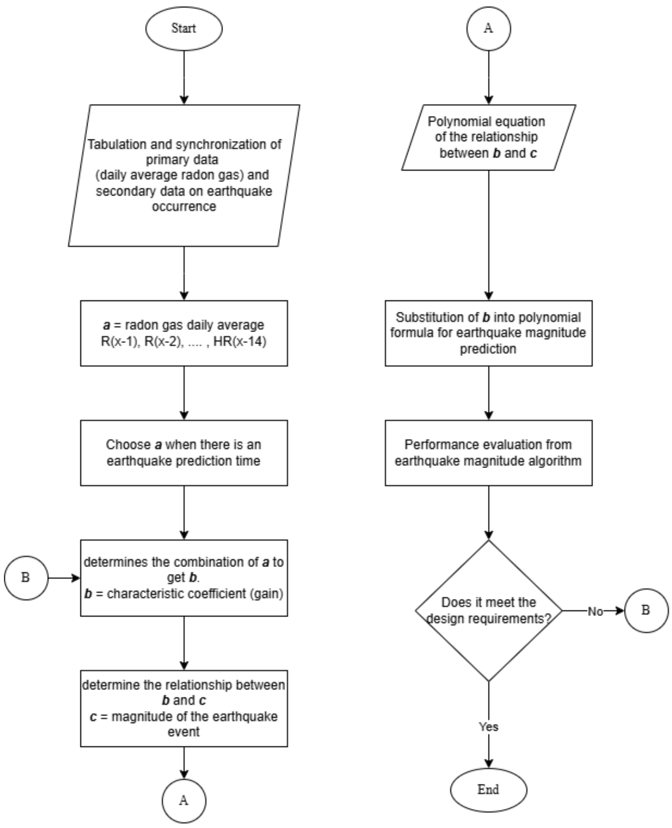

Figure 2. Magnitude prediction algorithm determination flowchart

Algorithms that have completed the determination stage are subsequently tested. The testing phase occurred from April 1, 2022, to May 30, 2024, at the Pacitan radon gas concentration telemonitoring station. This testing aims to identify the best algorithm according to the specified criteria. The best algorithm is then implemented in the server cloud and sends the notification to Telegram via the Telegram API. Thus, earthquake magnitude predictions can be automatically made based on the designed algorithm using radon gas concentration measurements for one to four days later between the Eurasia and Indo-Australia Plates with a magnitude above M4.5.

3. RESULTS AND DISCUSSION

In this section, we report the earthquake magnitude prediction when there is an alert from Thomas Oka's earthquake date prediction for the radon gas telemonitoring station in Pacitan [27]. When the earthquake date prediction alarm is active, data on Radon gas concentration is collected for magnitude prediction calculation. Based on the data processing results conducted according to the research flow in Figure 2, three gains were selected: Gain A (|R(x-7) – HR(x-7)|), Gain B (|R(x-3)-HR(x-7)|), and Gain C (|R(x-7)-R(x-1)|). The relationship between these gains and the actual earthquake magnitude was determined using polynomial equations. In this study, three polynomial degrees were used: 6th degree (Gain 1), 5th degree (Gain 2), and 4th degree (Gain 3) for each Gain (A, B, and C). This results in Gain 1A, Gain 2A, Gain 3A, Gain 1B, Gain 2B, Gain 3B, Gain 1C, Gain 2C, and Gain 3C. Predicted earthquake magnitude values were generated by substituting the gains into the equation. These predictions were then evaluated for both training and test data. Gains 3A, 1B, and 1C were excluded from the summary because they produced poor results, with predictions exceeding M10, a value that is not possible for earthquake magnitude scales.

The performance evaluation results for the training data are shown in Table 4. From this Table 4, it is evident that Gain 2B has the lowest evaluation performance for the MAE (0.37), MAPE (0.07), RMSE (0.61), MSE (0.37), and SMAPE (0.07) parameters, while its complex normalized mean absolute percentage error (cnMAPE) value is the highest (0.96), the same as Gain 3B. Additionally, it has the lowest absolute standard deviation (0.35) and relative standard deviation (0.51) compared to the other gains. Therefore, Gain 2B is the gain with the best evaluation for the training data compared to the other gains. The equation for Gain 2B is shown in (1), where *x* is the gain.

Table 5 presents the performance evaluation results of the equations used to predict earthquake magnitude using test data. From this Table 5, it can be seen that Gain 3B has the lowest evaluation values for MAE (0.30), MAPE (0.06), RMSE (0.55), MSE (0.30), and SMAPE (0.06), while its cnMAPE value is the highest (0.97), the same as Gain 2C. Additionally, it has the lowest absolute standard deviation (0.28) and relative standard deviation (0.40) compared to the other gains. Therefore, Gain 3B is the gain with the best evaluation for the test data compared to the other gains. The equation for Gain 3B is shown in (2), with x is Gain 3B.

The MAE, MAPE, RMSE, MSE, SMAPE, error absolute average (EAA), and error relative average (ERA) values for earthquake magnitude prediction using the statistical method are close to 0, and cnSMAPE is close to 1. This indicates that the earthquake magnitude prediction model based on radon gas concentration telemonitoring data is acceptable. The model demonstrates good prediction performance and can be considered reliable for practical applications in earthquake prediction.

$$M_{pred,\ Gain\ 2B} = -1E\text{-}09x^5 - 3E\text{-}07x^4 + 5E\text{-}05x^3 - 0.0022x^2 + 0.0276x + 5.1 \quad (1)$$

$$M_{pred,\ Gain\ 3B} = -2E\text{-}09x^5 + 7E\text{-}07x^4 - 7E\text{-}05x^3 + 0.0034x^2 - 0.0665x + 5.5134 \quad (2)$$

Table 4. Performance evaluation of data training set

	MAE	MAPE	RMSE	MSE	SMAPE	cnSMAPE	Stdev absolut	Stdev relatives
Gain 1 A	0.64	0.12	1.17	1.37	0.15	0.92	0.90	1.03
Gain 2 A	0.54	0.10	0.73	0.54	0.13	0.93	0.81	0.93
Gain 2 B	**0.37**	**0.07**	**0.61**	**0.37**	**0.07**	**0.96**	**0.35**	**0.51**
Gain 3 B	0.42	0.08	0.65	0.42	0.08	0.96	0.37	0.55
Gain 2 C	0.88	0.17	0.94	0.88	0.12	0.94	2.12	2.22
Gain 3 C	0.62	0.12	0.79	0.62	0.17	0.92	0.95	1.13

Table 5. Earthquake magnitude prediction data test error evaluation

Error index	MAE (s)	MAPE	RMSE	MSE	SMAPE	cnSMAPE	EAA	ERA
Gain 1 A	0.81	0.15	0.90	0.81	0.33	0.84	0.81	0.61
Gain 2 A	0.50	0.10	0.71	0.50	0.11	0.94	0.50	0.29
Gain 2 B	0.40	0.08	0.63	0.40	0.10	0.95	0.40	**0.10**
Gain 3 B	**0.30**	**0.06**	**0.55**	**0.30**	**0.06**	**0.97**	**0.30**	-0.11
Gain 2 C	0.35	0.07	0.59	0.35	0.07	0.97	0.35	-0.16
Gain 3 C	0.36	0.07	0.60	0.36	0.07	0.97	0.36	-0.17

We analyzed the error value during the model evaluation process, representing the disparity between the actual and predicted magnitudes. Figure 3 presents the boxplot of the error evaluation for the data test. Magnitude predictions using Gain 1A and Gain 2A models have a wide error distribution. All models have outlier errors visible at points outside the quartile limits. In Gain 1A and Gain 2A, there are several significant outliers, indicating that in some cases, the errors can be very large. The models with Gain 2B, Gain 3B, Gain 2C, and Gain 3C have error distributions for the first quartile (Q1) around 0.1-0.2 while for the third quartile (Q3) around 0.3-0.4. The model using these gains has a relatively narrow IQR, indicating small, consistent, and controlled errors. The box plot further strengthens the model's ability to predict earthquake magnitude with a relatively low error range.

Furthermore, to analyze the signs of deviations produced by regressors in their predictions, Figure 4 shows histograms of data test errors for every model. A positive error indicates that the prediction was lower than the actual value, while a negative error indicates that the prediction was higher than the actual value. The method prediction shows a higher quantity of negative errors than positive ones (negative bias), as can be noticed in the histograms of Figure 4. Negative bias in the error frequency graph refers to the tendency of errors to lean towards lower values than the actual magnitude values. In the error frequency graph context, negative bias is reflected in a distribution of errors that tend to be too low or negative.

All models have the highest error frequency at -0.25. The Gain1A Figure 4(a) and Gain 2A error distributions tend to be centered around -0.50 to 0.00, with a peak at -0.25, but for Gain 2A, it is slightly more spread-out Figure 4(b). The Gain 2B Figure 4(c) and Gain 3B Figure 4(d) distributions are more centered, with a frequency peak at -0.25 with a frequency of 10. Gain 2 B and Gain 3 B have the narrowest error distributions with a frequency peak at -0.25 and a smaller error range, indicating more consistent predictions. Gain 2C Figure 4(e) and Gain 3C Figure 4(f) showed a wider error range, with a more even distribution across the error range, indicating that these predictions tend to be more variable and less consistent than Gain 2B and Gain 3B. Overall, Gain 2B and 3B show more stable and consistent performance than the other gain configurations, with smaller errors and a more centered distribution. This is in line with the results of the data test prediction performance evaluation in Table 6.

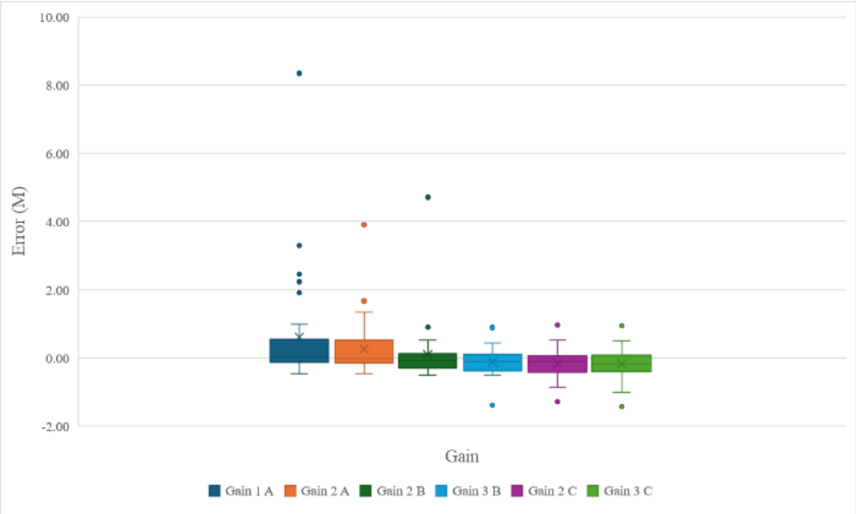

Figure 3. Data test boxplot error

Compared to other studies (Table 6) [13]-[17], [19], [29]-[49], magnitude predictions based on radon gas cloud data are rare, mostly using seismic data. Machine learning is not always better than statistical methods because machine learning methods use statistical calculations processed by machines/systems. The results of earthquake magnitude prediction show a comparison of earthquake magnitude prediction accuracy with differences in the main error metrics. The results of this research have a lower MAE and MAPE (0.30 and 0.06), indicating a smaller average absolute error and a more accurate percentage error than the research results using machine learning (MAE 0.33 and MAPE 6.03%). However, the results had lower RMSE and MSE (0.51 and 0.26), indicating smaller overall squared errors and more consistent predictions. The magnitude prediction results have identical SMAPE and cnSMAPE values (0.06 and 0.97), indicating similar performance in symmetric percentage error. If the focus is on absolute error, the results of this research are superior. In contrast, if the squared error is emphasized, the research results using machine learning methods are more optimal [42].

To advance earthquake prediction efforts, it is essential to develop new algorithms tailored to predicting earthquake magnitudes in various locations, as radon gas concentration characteristics differ by region. While challenges persist in forecasting rare high-magnitude earthquakes, this study marks a significant step forward. Future research should focus on integrating additional data to reduce prediction error, especially for magnitudes above M6 with rare events Figure 5, and for predicting the specific area of earthquake prediction in Indonesia, enriching the understanding of earthquake prediction and emphasizing improving methodologies in Indonesia.

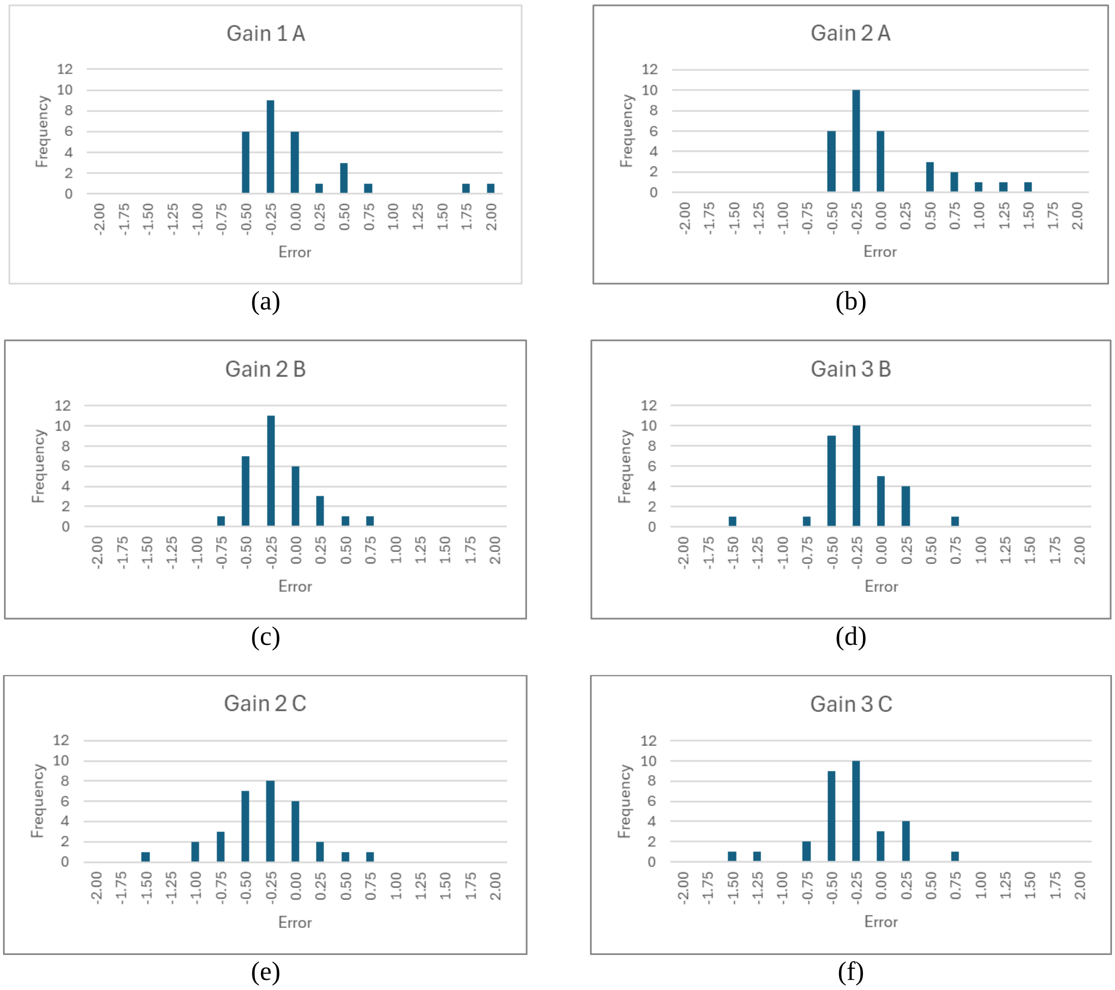

Figure 4. Error frequency of (a) Gain 1A, (b) Gain 2A, (c) Gain 2B, (d) Gain3B, (e) Gain 2C, and (f) Gain 3C

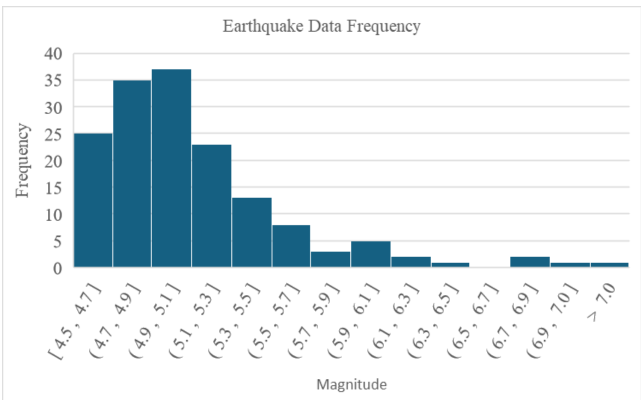

Figure 5. Earthquake data frequency

Table 6. Previous research results

Ref.	Key predictors	Methods used	Prediction scope	Performance highlights
[13]	Animal, environmental, and chemical indicators	BRBES	12 hours, Magnitude >6.5	Superior prediction (AUC=0.969), outperforming FLBES and ANN
[19]	Seismic data	Expert system	Varied magnitude (M0.1–M5.9)	Limited accuracy (<70%)
[14]	Seismic activity	Expert system	Global coverage, 12-hour interval, M3.6–M9.1	Exceptional accuracy (100%)
[15]	Meteorological, seismic data	Support vector regression	Monthly forecast	Precision (96% magnitude), moderate accuracy (78% count)
[16]	Seismic parameters	Neural networks, Random Forest	Monthly, Hindukush region, M≥5.5	Moderate accuracy: Training (79%), Testing (65%)
[17]	Big data seismic parameters	Regression models	Weekly, California, M3–M7	Low errors across magnitudes (MSE <0.79, MAE<0.59)
[30]	Seismic measurements	Multilayer perceptron	Short-term, M>4 classification	Moderate accuracy (73.8%)
[31]	Seismic electric signals (SES)	Artificial neural networks	Days, Greece, M≥5.2	Good overall accuracy (84%), reduced for high magnitudes (58%)
[32]	Seismic variables	Adaptive neuro-fuzzy system (ANFIS)	Iran, M>5.5	Strong model performance (R^2=0.94, RMSE=0.173)
[33]	Seismic data	Probabilistic neural network	Monthly, California, multi-class magnitudes	Reliable (R score: 0.62–0.78)
[34]	Historical seismic events	Neural network	Monthly, Taiwan, M≥6	Low predictive capability (R score=0.303)
[35]	Seismic data	Classifier ensembles	5 days, Chile, M4–M7	Varied sensitivity (46–90%), excellent specificity (89–100%)
[36]	Seismic data	SVM, Naïve Bayes	Daily, Indonesia	Moderate prediction errors (RMSE=0.751, MAE=0.598)
[29]	Radon time-series data	ML techniques (XGBoost, SVM, RF)	Short-term (1–4 days), Java, M>4.5	XGBoost best (MAE=0.33, RMSE=0.51)
[37]	Turkish seismic data	LSTM, CNN, ARIMA	36-month, Turkey	LSTM most effective for long-term magnitude prediction
[38]	Climate, seismic data	LSTM, Transformer	Japan, Indonesia, Himalaya, magnitude frequency	High accuracy (MAE=0.066, MSE=0.007)
[39]	Geospatial seismic features	Random forest classifier	Turkey, Himalayan region	Moderate accuracy (62.9%), balanced precision and recall
[40]	Geomorphological indicators	MLP neural network	Vietnam fault region, maximum magnitude	Strong predictions (R^2≈0.87, RMSE≈0.10)
[41]	Magnitude, spatial coordinates	VMD-BP neural network	Tibet, Yunnan, M>4	High accuracy (R^2≈0.93), superior to traditional BP
[42]	Seismicity parameters	hDCA, SVM, KNN, BPNN	Monthly, Sichuan, China, M>4.5	hDCA excellent (precision=0.73, AUC=0.97)
[43]	Fault density, depth, spatial features	Deep neural networks, SVM	Weekly, Iran-Himalayan region, multi-class magnitudes	Excellent specificity (≥90%), strong precision (81–88%)
[44]	Global seismic data	K-means enhanced ANN	Weekly, Global, M≥5.5	High positive predictive value (96%)
[45]	Seismic risk parameters	ML models (RF, XGBoost, ANN)	Turkey earthquake risk mapping	ANN very effective (MAE=0.176, RMSE=0.181, R^2≈1)
[46]	Seismic structure parameters	ANN, Tabu-search	General earthquake design parameters	Low errors (MAE=0.081, RMSE=0.116)
[47]	Electromagnetic, vibration signals	CNN with 3D features	Multi-class magnitude classification	Excellent precision (97%), recall (98%)
[48]	Seismic event data	CNN-BiLSTM hybrid	Japan, China, Magnitude 4.5–6	Moderate overall accuracy (69%), varying sensitivity
[49]	Bangladesh seismic indicators	Logistic regression, SVM	Bangladesh, Magnitude ≥5.0	Logistic regression superior (≈89% accuracy)

4. CONCLUSION

The research findings confirmed the efficacy of the statistical method in forecasting earthquake magnitudes using radon cloud data with Gain 3B, achieving the lowest error values across several evaluation metrics: MAE (0.30), MAPE (0.06), RMSE (0.55), MSE (0.30), SMAPE (0.06), cnMAPE (0.97), EAA (0.3), and ERA (-0.11), demonstrating smaller errors and more centralized distribution. These findings confirm the implementation of the statistical model in the server cloud of the earthquake early warning system, which can provide more accurate and timely predictions above M4.5. By improving the accuracy of prediction, this model enhances emergency preparedness, supports public education on safety measures, and equips responders with tools to manage earthquake-related disasters. The findings of this research are a very strong foundation for further developments in the field of refinement of forecasting models and strengthening early warning systems to mitigate seismic events.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data supporting this study's findings are available on request from the corresponding author thomas.o.p@ugm.ac.id. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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