International Journal of Advances in Applied Sciences (IJAAS)
Vol. 14, No. 1, March 2025, pp. 39~45
ISSN: 2252-8814, DOI: 10.11591/ijaas.v14.i1.pp39-45

Earthquake epicenter prediction from the Java-Bali radon gas telemonitoring station using machine learning

Christophorus Arga Putranto, Sunarno, Faridah, Thomas Oka Pratama
Sensor and Tele-control Laboratory, Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Sleman, Indonesia

Article Info

Article history:

Received Mar 21, 2024
Revised Sep 29, 2024
Accepted Oct 8, 2024

Keywords:

Early warning system
Earthquake prediction
Location
Machine learning
Radon

ABSTRACT

Predicting the location of earthquake epicenters is a critical aspect of earthquake forecasting, as it complements efforts to determine the time and magnitude of seismic events. This research addresses the challenge posed by the uncertainty in epicenter locations, particularly along the extensive plate faults of Indo-Australia and Eurasia. In these regions, effective earthquake prediction is compromised without accurate epicenter information, impeding mitigation strategies and complicating disaster impact estimation. The primary objective of this study is to devise an algorithm for forecasting earthquake epicenter locations by harnessing variations in radon gas concentrations on southern Java Island, Indonesia, as a predictive precursor. Using a supervised machine learning approach, this study integrates radon gas concentration data to predict the distance between a radon gas telemonitoring station and the impending earthquake epicenter. Three distinct machine learning algorithms were evaluated using data from six Java-Bali radon gas telemonitoring stations within an early warning system. The random forest algorithm emerged as the most effective, yielding an average root mean square error of 453.10 kilometers. The findings of this research significantly contribute to earthquake risk mitigation efforts. This work enhances our capability to anticipate seismic events, and more effective disaster preparedness and response strategies in earthquake-prone regions.

Corresponding Author:

Sunarno
Sensor and Tele-control Laboratory, Department of Nuclear Engineering and Engineering Physics
Faculty of Engineering, Universitas Gadjah Mada
Bulaksumur, Depok, Sleman Regency, Special Region of Yogyakarta 55281, Indonesia
Email: sunarno@ugm.ac.id

1. INTRODUCTION

Earthquakes are among the most deadly and dangerous natural disasters, mainly caused by tectonic activity between the earth's plates. Despite many efforts to understand and predict earthquakes, accurate prediction remains a significant challenge in geophysical science. The lack of references, methods, models, calculations, indicators, and information needed for earthquake prediction is a significant obstacle to overcoming this complex phenomenon [1], [2]. One approach in efforts to predict earthquakes is to look for indicators or precursors that can provide initial clues that an earthquake will occur. Some known indicators include natural events, atmospheric conditions, groundwater fluctuations, gas emissions in the soil, and animal responses. Among these precursors, fluctuations in radon gas emissions in soil have attracted attention, and several studies have linked them to potential as an earthquake indicator. For example, radon

gas precursors have been observed as earthquake precursors by Urumu Tsunogai and colleagues in the Kobe, Japan, earthquake in 1995 [3]–[10].

The radon gas monitoring can potentially observe the environment as a precursor to earthquakes. This method can be simulated in the laboratory or carried out long-term with direct observation through various devices and sensors [6]–[8], [11]–[16]. The early warning system engineering physics research team at Universitas Gadjah Mada has researched using multi-device observation stations spread around Yogyakarta, Indonesia. The radon gas data collected from these stations is vital for developing an earthquake early warning system. However, radon gas data has unique and different properties between observation stations, which demands reliable methods to produce accurate predictions [2].

Machine learning methods are one promising solution to overcoming the complex earthquake prediction problem. Although earthquake prediction with a high level of accuracy is still a challenge, several studies have succeeded in predicting the time of earthquake occurrence by taking radon gas concentration data for the next few days as input [3], [10], [17]–[20]. However, few studies can still predict earthquakes' location based on radon gas precursors. Several studies have tried to predict the location of earthquakes by utilizing historical data on earthquake events, taking depth and magnitude as the main features [21].

Research by Pratama *et al.* [3], one of the earthquake early warning system research teams has developed a statistical method for predicting the time an earthquake will occur. This method can produce an accuracy of 75% in setting an earthquake alarm 1 to 4 days after the alarm is active [2]. In this research, the main objective is to complement the Pratama *et al.* approach by predicting the location of the earthquake epicenter [3]. Predicting the location of the epicenter has a central role in early warning of earthquakes, especially in earthquake-prone areas such as the meeting of the Indo-Australian and Eurasian plates. Radon gas concentration data and machine learning methods are critical elements in predicting the location of the earthquake epicenter proposed in this research. Hopefully, this research can contribute to reducing the impact of natural disasters caused by earthquakes.

2. RESEARCH METHOD

In the method section, this research will outline the basic concepts of three ensemble learning techniques essential in machine learning: gradient boosting, AdaBoost, and random forest. The sequence of this research is data collection, dataset pre-processing, machine learning modeling, and model selection based on the best root mean square error (RMSE). Distance results from the model with the lowest RMSE will be used as the prediction. The research method diagram can be seen in Figure 1.

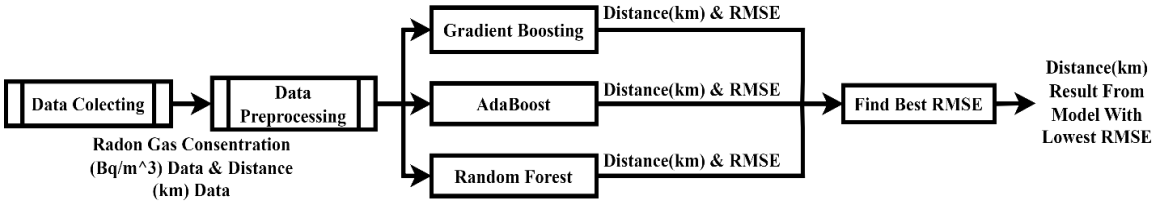

Figure 1. Block diagram of research methods

2.1. Data collection

The research employed a comprehensive data collection strategy incorporating primary and secondary sources. Primary data, crucial to the study, consisted of daily average radon gas measurements obtained from six telemonitoring stations: Pacitan, Bantul, Prambanan, Maguwo, Serang, and Bali. This dataset comprised 14 data points, specifically the daily average radon gas concentration (Bq/m^3), offering a robust depiction of the variances in radon gas levels throughout the designated period. Complementing the primary data, secondary data was sourced from the Potsdam Geofon site, providing essential information about the coordinates of earthquake epicenters. These coordinates underwent conversion using the Haversine formula to derive distance values between the earthquake epicenter and each telemonitoring station. The combination of primary and secondary data is the basic training material for the supervised machine learning process. This machine learning approach aimed to predict the distance from each telemonitoring station to the impending earthquake epicenter, enhancing the precision and efficacy of earthquake epicenter location forecasting. The 224 data collection period for radon gas and earthquakes starts from January 20, 2022 to April 30, 2023.

2.2. Data pre-processing

Data pre-processing for primary and secondary data is carried out before entering the machine learning process. The data will be cleaned from null, empty data, missing values, and outliers that can influence prediction results. Removing outliers where data points far from most other data are identified and removed. Outliers were removed based on the z-score value, with 5% of the z-score as outliers from the entire average radon gas concentration data per telemetry station. Therefore, a 95% z-score of the whole data from each station will be used. The data preprocessing process resulted in features in the form of a clean dataset. The dataset is divided into two parts: features (X), the primary data variables used as features to predict the target variable, and target (y), which is the distance of the target to predict. The dataset is further divided into two subsets: a training set and a testing set. The training set (80%) while the testing set (20%). This split ensures that the model is trained on one data set and tested on another set it has not seen before. The machine learning modeling process can be carried out with the training and test data. The data processing steps are presented in Figure 2.

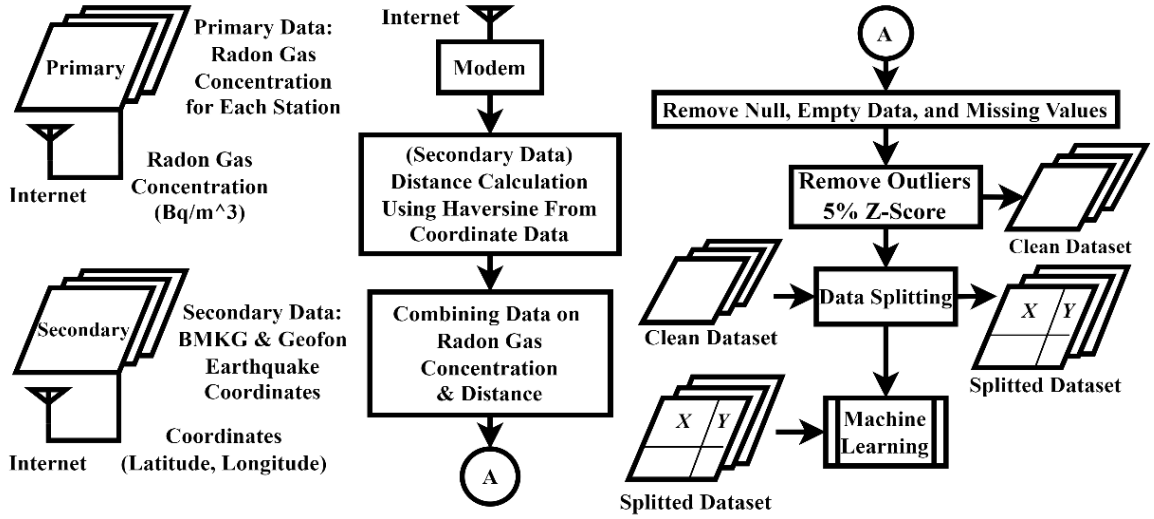

Figure 2. Data acquisition and pre-processing

2.3. Machine learning

The main difference between gradient boosting, AdaBoost, and random forest is how they combine weak models. Gradient boosting focuses on gradually reducing prediction errors by improving previous models, AdaBoost gives more weight to misclassified samples, while random forest combines predictions from many decision trees in parallel. The appropriate technique selection depends on the problem to be solved and the data characteristics used. In this research, we will compare the performance of these three techniques in the context to see the strengths and weaknesses of each model [16], [22]–[26].

2.4. Method implementation

2.4.1. Algorithm training

After the data pre-processing stage, the data will be separated into two subsets, namely train data and validation data, through the data separation stage. Train data is used to train the model, while validation data is used to measure the model's performance during training and help in parameter tuning. The final stage in the training process is machine learning training, where the selected algorithm will be applied to the train data and adjusted to the patterns in the data. This process will be repeated and adjusted with various parameters until the model achieves performance that meets the research demands. Going through this series of stages carefully ensures that the resulting machine-learning model can provide accurate and useful predictions.

2.4.2. Gradient boosting implementation

Gradient boosting implementation consists of several crucial stages. The first stage is selecting the base model to be used. It used a decision tree (decision trees) as a base model known as gradient boosting with decision trees or gradient boosted trees (GBT). The second step is the initialization of the GBT model.

Initially, this model will have equal weights for all training data. Then, it will run iterations to produce several decision trees. Each iteration trains a decision tree using the gradient of the loss function against the previous prediction. This will give greater weight to data that earlier models had difficulty explaining. Furthermore, each newly added decision tree will have its weight in the ensemble model. It is combining predictions from all decision trees possible to produce a final prediction. It will also pay attention to essential parameters such as learning rate and tree depth to control model complexity [25], [27], [28].

2.4.3. AdaBoost implementation

In the implementation phase of AdaBoost, the steps in implementing this technique are followed carefully. The weak model is chosen as the base model, with a decision tree that has limited depth as the choice, which will be adapted adaptively during the training process. Next, weight initialization is carried out for each training data sample, emphasizing misclassified samples at each iteration. The weights for each sample are initially set uniformly. Iterations are carried out, where the base model is trained on the training data with weights adjusted adaptively. Samples misclassified in the previous iteration will be given greater weight in the next iteration. This iteration continues until the specified number of iterations is reached or a sufficient accuracy level is achieved. Finally, predictions from all base models are combined using weights appropriate to each model. The final result of this ensemble is an AdaBoost model that has been trained to predict the distance to the epicenter of an earthquake from telemonitoring station data [22], [29], [30].

2.4.4. Random forest implementation

In the random forest implementation phase, the steps are carefully guided to produce a reliable ensemble model. First, choose the number of decision trees that will form the ensemble and other parameters, such as the number of random features used in each tree. The second step is to create a random data sample set with replacement from the training dataset for each tree. This ensures variation in the data used to train each tree, helping to avoid overfitting. Each decision tree is trained on a dataset that has been created. Separation criteria such as Gini impurity or entropy to build an optimal decision tree at each iteration [16], [26], [31], [32]. During testing, it uses validation data sets to measure the performance of each tree separately. Finally, the predictions from each tree will be combined via majority vote (classification) or average (regression) to produce a final ensemble prediction.

3. RESULTS AND DISCUSSION

One of the important metrics used in the evaluation process is RMSE. During the evaluation, all models were trained on the validation dataset and measured the RMSE of each model. To choose the best algorithm for implementing epicenter distance prediction, the model with the smallest RMSE is selected, namely the model with the highest accuracy level in predicting this distance. Choosing the best algorithm is essential in ensuring that the epicenter distance prediction to be implemented has a high level of accuracy and is reliable. Thus, the machine learning model evaluation results are the basis for selecting a model that will be used for distance prediction in the context of radon gas telemonitoring stations.

Following the training phase utilizing gradient boosting, AdaBoost, and random forest machine learning models, the dataset was split into 80% (179 data) for training data and 20% (45 data) for testing data to assess the models' predictive capabilities. All three models demonstrated proficiency in predicting the distance between the earthquake epicenter and the telemetry station. The prediction performance indicators were evaluated based on the outcomes of distance prediction tests conducted with the trained machine learning models. The AdaBoost model consistently yielded the most favorable RMSE results, signifying superior predictive accuracy. The detailed RMSE values for each radon gas telemonitoring station under each machine-learning algorithm are presented in Table 1. Additionally, the corresponding RMSE training results from each radon telemonitoring station are visually represented in Figure 3, providing a comprehensive overview of the model's performance across different stations. These findings contribute valuable insights into the comparative effectiveness of the machine learning algorithms in predicting earthquake epicenter distances, which is crucial for refining and optimizing future predictive models. Based on the prediction results obtained, it can be seen from Figure 3, that each station has a different best algorithm. The best algorithm at Pacitan station is AdaBoost; at Bantul station is random forest; at Prambanan station, it is AdaBoost; at Maguwo station is random forest; at Serang station, it is gradient boosting; and at Bali station, it is random forest. In general, average RMSE is used to find the best model; the Random Forest algorithm is the best algorithm for all radon gas telemetry stations, but need to pay attention again because each station has a different best algorithm, so random forest cannot be used as an absolute reference algorithm.

Table 1. RMSE predicted distance to the epicenter and radon gas telemonitoring station

Station	AdaBoost (AB) RMSE (km)	Gradient Boosting (GB) RMSE (km)	Random Forest (RF) RMSE (km)
Pacitan	470.79	499.61	484.22
Bantul	536.13	555.00	498.30
Prambanan	540.73	577.15	580.51
Maguwo	610.56	697.87	590.58
Serang	151.74	118.88	162.37
Bali	739.17	787.81	402.62
Average	508.19	539.39	453.10

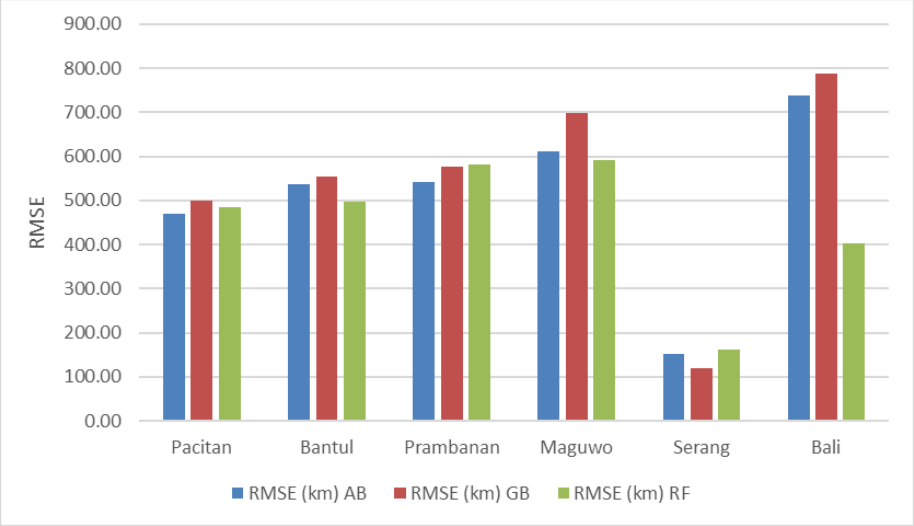

Figure 3. Graph of RMSE predictions from each station

4. CONCLUSION

Earthquakes remain a formidable challenge in geophysical science despite extensive research efforts to understand and predict them. from testing the algorithm for predicting the distance of the earthquake epicenter from 6 Java-Bali radon gas telemonitoring stations on an early warning system using three types of machine learning (gradient boosting, AdaBoost, and random forest). The optimal algorithm varied across different stations, indicating the importance of considering station-specific characteristics when implementing predictive models. It was concluded that the best algorithm was random forest with an average RMSE value of 453.10 kilometers. Overall, the findings contribute valuable insights into the potential of machine learning methods for enhancing earthquake prediction accuracy. By refining predictive models and considering station-specific factors, such as geological conditions and data variability, researchers can further advance early warning systems and mitigate the impact of seismic events on vulnerable communities.

ACKNOWLEDGEMENTS

Thank you to the Sensor System and Tele-Control Laboratory research team at the Department of Nuclear Engineering and Physical Engineering, Universitas Gadjah Mada, Indonesia, for providing a radon gas telemonitoring system. Thank you to Potsdam Geofon and the Indonesian Meteorology, Climatology, and Geophysics Agency, for providing earthquake data. We express our deepest gratitude for the support of the Directorate of Research, Technology and Community Service, Directorate General of Higher Education, Research and Technology, and Ministry of Education, Culture, Research, and Technology as providers of financial support with SK number 0536/E5/ PG.02.00/2023.

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BIOGRAPHIES OF AUTHORS

Christophorus Arga Putranto, S.Si. is a Master Student of the Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering at Universitas Gadjah Mada in 2021. He also received his S.Si. (Electronics and Instrumentation) from Universitas Gadjah Mada in 2015. His research includes a telemonitoring system and earthquake prediction based on the radon gas concentration. He can be contacted at email: christophorus.arga.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 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

Dr. Faridah, S.T., M.Sc., IPU. is an Associate Professor in the Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering at Universitas Gadjah Mada since 1999. Her doctoral degree is in Environmental Science, from Universitas Gadjah Mada, and focuses on Indoor Environmental Quality comfort. She got an S.T. from Engineering Physics, Institut Teknologi Sepuluh Nopember, and an M.Sc. from the Microelectronics Program, at Nanyang Technological University. She was involved in several research topics; pattern recognition, instrumentation in power plants, and also sustainable building. Her current research interests are sensors and instrumentation. She can be contacted at email: faridah@ugm.ac.id

Thomas Oka Pratama, S.T., M.Eng. earned a Doctorate in Environmental Science from Universitas Gadjah Mada in 2021, having previously obtained his S.T. and M.Eng. degrees (in Engineering Physics) from the same institution in 2014 and 2021, respectively. Presently, he serves as a lecturer in the Engineering Physics Program at the Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Indonesia. His research interests encompass the development of telemonitoring systems and earthquake prediction methods utilizing radon gas concentration and groundwater levels. For inquiries, he can be contacted at email: thomas.o.p@ugm.ac.id.