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# Random Forest Analysis for Predicting the Probability of Earthquake in Indonesia

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**Abstract:**

This research focuses on identifying risk zones by applying the Random Forest algorithm to predict the probability of earthquakes in Indonesia. The selection of this algorithm is based on its capacity to process voluminous, intricate, and non-linear data, which is frequently encountered in the context of seismic studies. In this study, a predictive model is constructed using historical earthquake data and geographic coordinates. The primary objective is to evaluate the effectiveness of the Random Forest algorithm in predicting earthquake probabilities across different regions of Indonesia. The analysis results indicate that the highest likelihood of earthquakes occurs in Maluku at 24.77%, followed by Nusa Tenggara at 18.34% and Sulawesi at 18.68%. The Random Forest algorithm achieved an accuracy rate of 90.78% in the prediction model, demonstrating its effectiveness in forecasting earthquake probabilities. These findings are expected to provide valuable insights for the government and stakeholders to develop improved disaster mitigation strategies in Indonesia. Furthermore, the methods used in this study can be applied to predict the probabilities of various types of natural disasters across different regions. on using larger datasets and examining the specific regions from which the data is collected.

**Keywords:** Random Forest, Prediction, Earthquake, Risk Zone.

## Introduction:

Earthquakes are a type of natural disaster that often result in substantial damage to human life and the environment. Such damage may include soil liquefaction, landslides, and tsunamis. Despite the complex and unpredictable nature of earthquakes, their associated risks can be mitigated [1]. Indonesia provides an optimal setting for studying earthquake risks, given its location at the boundary of three major tectonic plates, which renders it seismically active and susceptible to environmental damage [2]. In recent years, the country has sustained significant damage from earthquakes and tsunamis, emphasizing the necessity for reliable prediction models. By enhancing our comprehension of the patterns and distribution of earthquakes in Indonesia through these models, it will become more straightforward to identify areas that may be at risk.

Previous research has employed various methods to predict potential seismic risks in Indonesia. An adaptive neural fuzzy inference system has been used for the spatial analysis of magnitude distribution [3]. Moreover, neural networks and analytic hierarchy process have been used to quantify the risk to urban populations posed by earthquakes [4]. However, the Random Forest method offers significant advantages over other techniques. It is particularly adept at managing complex data and facilitating the analysis of results by revealing non-linear interrelationships between variables that affect earthquake risk in different regions. As an ensemble learning technique, Random Forest combines multiple decision trees to reduce overfitting and improve prediction accuracy [5]. This is advantageous for predicting the likelihood of earthquakes. Previous research demonstrated that Random Forest achieved the highest accuracy in predicting earthquake types in India [6]. The superiority of this method was also confirmed in similar studies in South Korea [7] and China [8], which validated its effectiveness in the seismic context.

Most previous studies have concentrated on classifying areas by the levels of earthquake hazard. However, this study places greater emphasis on predicting the probability of areas most susceptible to earthquakes and the magnitude of such events. Nevertheless, there are inherent limitations and challenges in estimating the likelihood of areas in Indonesia that are prone to earthquakes. One of the primary limitations is the reliance on earthquake data of varying quality and availability, which can significantly impact the accuracy of predictions. Another challenge is the integration of data from diverse sources and the development of optimal prediction models to enhance the reliability of these predictions. Nevertheless, the most crucial aspect of improving prediction quality remains the integration and validation of data from a range of sources.

The primary shortcoming addressed by this research is the lack of a comprehensive methodology for identifying earthquake-prone regions, particularly in Indonesia. Furthermore, the lack of integration between seismic and geological data has resulted in less accurate prediction models. Consequently, this research project aims to address the gap by developing an earthquake prediction model in Indonesia using the Random Forest algorithm, which is expected to yield more accurate estimates of earthquake probabilities. This approach is designed to enhance the understanding of seismic risk in Indonesia. The resulting model will not only provide earthquake probability estimates but also demonstrate the superiority of the Random Forest algorithm in identifying earthquake-prone areas. Therefore, the findings of this research are expected to serve as an effective tool for decision-making related to disaster mitigation.

## Methodology:

The data utilized in this study are secondary data obtained from the Kaggle website, which is sourced from the Indonesian Meteorology, Climatology and Geophysics Agency (BMKG) [9]. The data set includes geographic information, such as geographic coordinates, and seismic data, including earthquake history. This study aims to develop a prediction model for earthquake-prone areas in Indonesia using decision trees. The model employs the Random Forest algorithm to assess the likelihood of major earthquakes occurring across various regions of Indonesia using an analysis of key geographic and seismic data.

This research proposes several hypotheses. Firstly, the Random Forest algorithm is hypothesized to accurately predict the likelihood of earthquake-prone areas in Indonesia by utilizing geographic and seismic data. Secondly, it is proposed that factors such as geographical coordinates, location, and the magnitude of past earthquakes can influence the prediction of these areas. Lastly, the study hypothesizes that the predictive model can assist in identifying earthquake-prone regions in Indonesia, facilitating effective disaster mitigation planning.

The following section outlines the methodology and steps involved in this research, as illustrated in Figure 1.

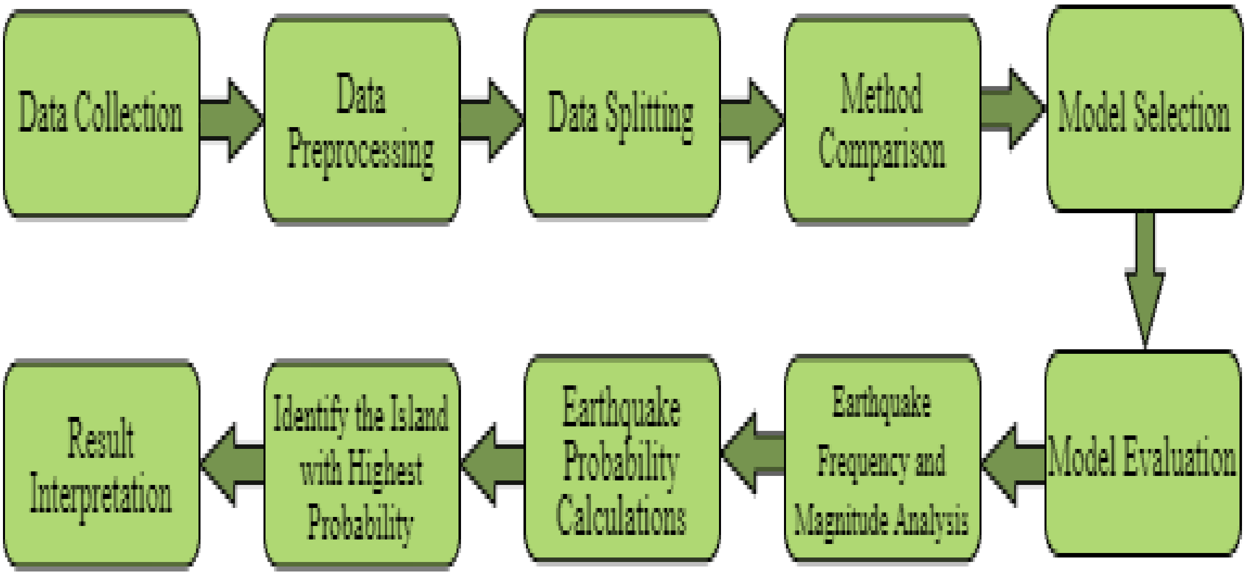


**Figure 1. Step Chart in the Methodology**

1. Data Collection

Indonesian earthquake data was obtained from the Kaggle website which collects data from the Indonesian Meteorology, Climatology and Geophysics Agency (BMKG).

2. Data Preprocessing

Data preprocessing is an important stage to ensure the quality and consistency of the data before further analysis. This process involves the following steps:

2.1 Data Cleaning

The data cleaning process consists of 2 types: identifying data with missing or invalid values to be removed and removing data of the same value to reduce bias in the model.

2.2 Data Transformation

Some data features must be converted into the format required by the Random Forest algorithm. In this study, the geographical coordinates and magnitude features that were originally in text form were converted into numbers.

2.3 Data Standardization

Data standardization involves converting the data to have a mean of 0 and a standard deviation of 1. It aims to check if all the features in the dataset have a similar scale. The standardization formula is as follows Eq. 1 [10], [11]:

$$Z = \frac{(X - \mu)}{\sigma}. \quad (1)$$

Where:

- Z is the standardized data value
- X is the original data value
- μ is the average of the data
- σ is the standard deviation of the data

2.4 Data Normalization

Min-max normalization was utilized to standardize the data, ensuring uniformity within a specific range. This method converts each feature into a scale between 0 and 1, thereby preventing any single feature from dominating the analysis. Here is the normalization formula Eq. 2 [12], [13]:

$$X_{norm} = \frac{(X - X_{min})}{(X_{max} - X_{min})}. \quad (2)$$

Where:

- $X_{norm}$ is the normalized data value
- X is the original data value
- $X_{min}$ is the minimum value of the data
- $X_{max}$ is the maximum value of the data

3. Data Splitting

The dataset underwent division into training and testing sets using K-fold Cross-Validation with k = 10. This technique entails splitting the data into k random subsets (or folds), training the model on k-1 folds, and evaluating it on the remaining fold.

This cycle repeats 10 times, ensuring that each fold serves as a validation set exactly once.

4. Method Comparison

In this stage, the performance of several machine learning models, including CART, Random Forest, C4.5, GBM, and AdaBoost, will be compared to select the optimal method for predicting earthquake magnitude. Each model will be evaluated using metrics, including MSE, RMSE, NRMSE, and accuracy.

5. Model Selection

A comparative analysis evidenced that the Random Forest algorithm was selected for its capacity to process complex data sets, mitigate overfitting, and yield precise outcomes. In this study, the Random Forest algorithm comprises 100 independent decision trees, each selecting a random subset of training data to enhance prediction accuracy.

6. Model Evaluation

The model's performance is evaluated by testing the data and computing the average of evaluation metrics (MSE, RMSE, and NRMSE) obtained through k-fold cross-validation. Additionally, model accuracy is determined based on the average NRMSE value.

7. Earthquake Frequency and Magnitude Analysis

This analysis aims to determine the frequency and average magnitude of earthquakes on each island to identify islands exhibiting significant seismic activity. Islands experiencing fewer than 10 earthquake events were excluded from the analysis.

8. Earthquake Probability Calculation

This research will utilize a probabilistic model based on earthquake data to predict the likelihood of future earthquake events. The historical frequency of earthquakes on each island will be the primary variable in this model.

9. Identify the Island with the Highest Probability

The island with the highest probability of earthquake will be chosen based on a judgment derived from probability calculations. Key factors in this assessment will include historical earthquake frequency and the average magnitude of earthquakes.

10. Result Interpretation

An earthquake probability map for the Indonesian region will be presented as a result of the Random Forest model's predictions. Furthermore, this study assesses the model's performance using metrics including accuracy, RMSE, NRMSE, and MSE. An overview of the model's ability to forecast earthquake events will be given by the findings of this investigation.

The pseudocode to estimate the probability of earthquake-prone areas based on available data is as follows:

**Algorithm 1: The Random Forest Pseudocode for Earthquake Prediction Analysis**

**Input:** prediction, k

**Output:** avg_mse, avg_rmse, avg_nrmse, accuracy_reg, probabilities_per_island, max_prob_island

**Process:**

```
READ the earthquake data from the file "prediction.xlsx" INTO the data_table

FOR each data row IN data_table:

    IF there is empty data THEN

        DELETE that row

    END IF
```

```
END FOR
FOR each numeric column (latitude, longitude, depth):
    CALCULATE the average of the column values
    CALCULATE the standard deviation of the column values
    FOR each data in that column:
        STANDARDIZE data with Eq. 1
        NORMALIZE data Eq. 2
    END FOR
END FOR
DIVIDE the data_table into k = 10 parts randomly
FOR each piece of data:
    TAKE part of the data as training data
    TAKE the remaining part of the data as test data
    TRAIN a Random Forest model with training data
    FORECAST earthquake strength on test data
    CALCULATE prediction error (avg_mse, avg_rmse, avg_nrmse) and accuracy_reg
    SAVE calculation results
END FOR
CALCULATE the average prediction error of all parts of the data
FOR each island:
    COUNT the number of earthquakes on the island
    CALCULATE the average earthquake strength on the island
    IF the number earthquake is large enough THEN
        CALCULATE the probability of an earthquake on the island
        SAVE calculation results in probabilities_per_island
    END IF
END FOR
SEARCH for the island with the highest earthquake probability
```

SAVE search results in max_prob_island

SHOW analysis results

**Experiment Setup:**

The methodology was tested using a dataset from the Indonesian Meteorology, Climatology and Geophysics Agency (BMKG), sourced from the Earthquake Repository [9]. This dataset contains 92.887 records of earthquake events spanning from November 1, 2008 until January 26, 2023. However, for model training and validation, only data from 2015 until 2023, comprising 74.037 samples, were utilized. This time frame was chosen to ensure the relevance of recent data to current conditions and to streamline the data processing, as using the entire dataset would have been more complex. This choice also balanced the model's accuracy and algorithmic complexity, focusing on predicting the probability of earthquake risk zones in Indonesia rather than classifying regions based on earthquake hazard levels.

The original BMKG dataset included parameters such as the ‘event date’, ‘event timestamp (ot)’, ‘epicenter latitude (lat)’, ‘epicenter longitude (lon)’, ‘event depth (depth)’, ‘event magnitude (mag)’, and ‘event area (remark)’. In this study, the ‘date’ and ‘ot’ parameters were excluded, while ‘latitude’, ‘longitude’, ‘depth’, ‘remark’, and ‘magnitude’ were retained. Additionally, during the data processing phase, the parameters ‘timezone (indicating the time zone of the earthquake)’, ‘province (specifying the province where the earthquake occurred)’, and ‘island (indicating the island where the earthquake occurred)’ were added to facilitate region-based analysis.

This study aims to create a predictive model to estimate the probability of earthquake risk zones in Indonesia. The magnitude of earthquakes is treated as the target variable, while ‘latitude’, ‘longitude’, ‘depth’, ‘remark’, ‘timezone’, ‘province’, and ‘island’ are used as predictor variables. The random forest algorithm will leverage this data to predict the magnitude of each earthquake event in the dataset.

The model's performance will be assessed using the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Normalized Root Mean Squared Error (NRMSE) metrics. Mean Squared Error (MSE) measures the average of the squared differences between the observed and predicted values and is defined as follows in Eq. 3 [14], [15]:

$$MSE(\boldsymbol{x},\hat{\boldsymbol{x}}) = \sum_{i=1}^{n} \frac{(x_i - \hat{x}_i)^2}{n}. \quad (3)$$

Where n is the total number of observations (data points), $x_i$ is the actual value for the i-th observation, and $\hat{x}_i$ is the predicted value for the i-th observation.

While the Root Mean Squared Error (RMSE) is defined as Eq. 4 [16], [17]:

$$RMSE(\boldsymbol{x},\hat{\boldsymbol{x}}) = \sqrt{\sum_{i=1}^{n} \frac{(x_i - \hat{x}_i)^2}{n}}. \quad (4)$$

Where x is a vector of observed values, $\hat{x}$ is a vector of predicted values, and n is the number of elements of each vector.

NRMSE (Normalized Root Mean Squared Error) declared as Eq. 5 [18], [19]:

$$NRMSE(\boldsymbol{x},\hat{\boldsymbol{x}}) = \sqrt{\sum_{i=1}^{n} \frac{(x_i - \hat{x}_i)^2}{n}}. \quad (5)$$

$\hat{\boldsymbol{x}}$ here is the average of vectors x.

To provide readers with a simpler analysis, we calculated the accuracy as follows Eq. 6 [20]:

$$\%Accuracy = (1 - NRMSE) \times 100\%. \quad (6)$$

Where NRMSE is the Normalized Root Mean Squared Error.

**Numerical Result:**

In this section, we present the evaluation results of the various regression models tested. The evaluation is done based on the metric RMSE (Root Mean Square Error), MSE (Mean Square Error), NRMSE (Normalized Root Mean Square Error), and accuracy ((1 – NRMSE) × 100%).

**Table 1. Numerical Simulation and Data Sharing Results**

| Model | RMSE | MSE | NRMSE | Accuracy (%) |
|---|---|---|---|---|
| CART | 0.8695 | 0.7561 | 0.1072 | 89.28 |
| Random Forest | 0.7481 | 0.5597 | 0.0922 | 90.78 |
| C4.5 | 0.8695 | 0.7561 | 0.1072 | 89.28 |
| GBM | 0.7899 | 0.6239 | 0.0974 | 90.26 |
| AdaBoost | 0.7483 | 0.5600 | 0.0922 | 90.78 |

In Table 1. The outcomes of numerical simulations for different regression models tested on the dataset are displayed. The dataset was partitioned using the k-fold Cross-Validation method with k = 10, ensuring each of the 10 folds serves as testing data exactly once, with the remaining 9 folds used for training. This approach ensures comprehensive use of all data points for both training and testing thereby enhancing the reliability of the results.

**Predictive Model Accuracy:**

In Figure 2, the frequency, average magnitude, and probability of earthquakes for each island in Indonesia are presented based on the prediction results of the Random Forest model.

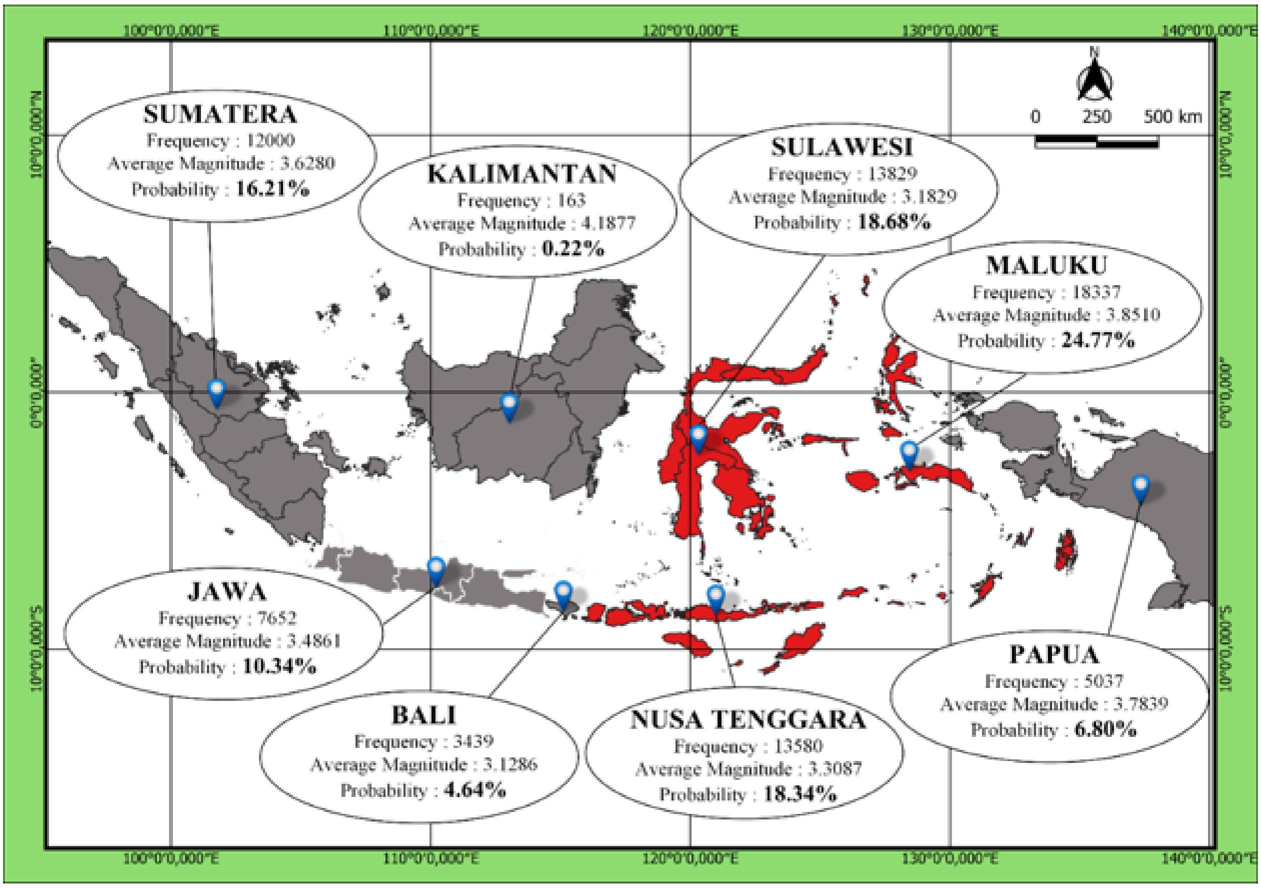


**Figure 2. Earthquake Probability in Each Island in Indonesia Based on Random Forest Model**

## Discussion:

In this study, we assessed the efficacy of various regression models in forecasting the earthquake magnitude of earthquakes in Indonesia. The models that were tested include CART, Random Forest, C4.5, GBM, and AdaBoost, with evaluation metrics such as RMSE, MSE, NRMSE, and accuracy. The results of the evaluation demonstrate that the Random Forest and AdaBoost models exhibited the most optimal performance, with RMSE values of 0.7481 and 0.7483, respectively, and an accuracy of 90.78%. Nevertheless, for practical applications, the preferred Random Forest model is preferable to the AdaBoost model.

The Random Forest model consistently outperforms other models across a range of evaluation metrics, demonstrating superior predictive ability about earthquake magnitude and high accuracy. One of the key advantages of Random Forest is its capacity to effectively handle data variation, a consequence of its ensemble nature, which combines predictions from multiple decision trees, thus reducing both bias and variance. Furthermore, the Random Forest model has demonstrated greater resilience to overfitting and outliers, making it a more dependable choice when handling complex data sets [21].

Furthermore, the Random Forest model offers insights into the features that influence earthquake magnitude predictions [22]. This information can facilitate more informed decision-making about earthquake risk mitigation. The probability map of earthquakes generated from the model predictions (Figure 2) illustrates the distribution of earthquake probabilities across Indonesia, the highest probability is observed in Maluku (24.77%), followed by Sulawesi (18.68%) and Nusa Tenggara (18.34%). In contrast, the lowest probability is recorded in Kalimantan (0.22%). This map provides a clear visualization of the earthquake probability distribution across different islands, which is highly useful for disaster mitigation planning.

While the results demonstrate that Random Forest exhibits robust performance, several limitations warrant further attention. Firstly, the model's performance is contingent upon the quality of the available data. The dataset utilized in this study is confined to data from 2015 until 2023. Consequently, predictive accuracy could be enhanced by employing a more expansive and heterogeneous dataset. Furthermore, the assumption that earthquake data is stationary should be reevaluated, given that earthquakes are complex phenomena and may exhibit changing patterns over time.

The results of this study align with those of previous literature, which also highlight Random Forest's strong performance in handling regression problems with diverse and non-linear data. Based on our literature review, Random Forest consistently outperforms other models such as CART and AdaBoost, which are more prone to overfitting and less effective in handling imbalanced data [8]. This study thus reinforces the evidence that Random Forest is one of the most effective models for earthquake prediction.

## Conclusions:

This research successfully evaluated the performance of several regression models in predicting the probability of earthquakes on each island in Indonesia using the BMKG dataset from 2015 until 2023 [9]. The results indicate that the Random Forest and AdaBoost models exhibited the highest levels of accuracy and favorable RMSE values. It can be concluded that the Random Forest model is the most effective for predicting earthquake magnitudes in Indonesia. The model demonstrates consistent performance, high accuracy, robust generalization capabilities, and resilience to outliers. Moreover, the Random Forest model provides valuable insight into the relative importance of features, which is essential for informed decision-making in earthquake risk mitigation. The findings of this research are of significant importance for disaster mitigation efforts in Indonesia. Improved earthquake magnitude predictions will enable the government and relevant institutions to enhance preparedness and response strategies, thereby reducing the adverse effects of earthquakes. Future research could focus on enhancing model accuracy by utilizing larger and more diverse datasets and exploring additional ensemble methods to strengthen predictions.

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