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Enhancing Earthquake Prediction using Machine Learning with Optimization Method

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Abstract
Earthquakes have complex seismic characteristics that make accurate classification challenging. This study proposes a machine learning approach that combines K-Means clustering and Random Forest to improve earthquake classification performance. We utilize earthquake records with numerical and geographic attributes, including date, latitude, longitude, magnitude, depth, and location. K-Means clustering groups the earthquake records into three clusters, interpreted as Dangerous, Medium, and Not Dangerous based on their seismic characteristics. We then apply Random Forest to classify the earthquake records and evaluate different numbers of trees using the F1-Score. The results show that Random Forest with 100 trees achieves the highest F1-Score of 87.21%, slightly outperforming SVM (87.11%), Decision Tree (86.24%), and Naïve Bayes (85.89%). We further analyze several feature combinations to identify the most informative attributes. The combination of Date, Latitude, Longitude, Magnitude, and Location produces the highest F1-Score of 93.23%, improving the performance by 6.02 percentage points compared with the initial Random Forest configuration. The results demonstrate that appropriate feature selection substantially improves earthquake classification performance. This study shows that integrating K-Means clustering, feature selection, and Random Forest provides an effective approach for earthquake classification based on seismic and geographic characteristics.

Keywords: Earthquake, Classification, K-Means, Random Forest, Machine Learning

1. Introduction

Earthquakes remain difficult to predict because their occurrence depends on complex and nonlinear interactions within the Earth. Conventional approaches often rely on seismological analysis, historical records, and predefined thresholds. These approaches provide useful information, but they do not always capture hidden patterns in large and heterogeneous seismic datasets. Machine learning (ML) offers an alternative because it can learn relationships between historical observations and earthquake-related characteristics. Several studies already use ML to predict earthquake magnitude, depth, seismic risk, or ground motion from geographic and seismic data [6], [14], [17]. However, prediction performance still depends strongly on the quality of the input data, selected features, and learning algorithm. This issue creates a need for optimized ML methods that can improve prediction accuracy while maintaining practical computational performance.

Recent studies show that ML can process earthquake observations more effectively than traditional approaches in several prediction scenarios. Jarah et al. use seismic catalogs from Iraq and neighboring regions and develop a neural network model from ground-vibration data. Their results indicate that the neural network performs better than other evaluated ML methods [7]. Zhu et al. also demonstrate that ML methods can outperform traditional statistical techniques when detecting hydrochemical anomalies associated with earthquakes. However, their results vary across hot springs and indicator

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types, while the model cannot clearly distinguish pre-earthquake anomalies from post-earthquake anomalies [8]. These findings show that ML has strong potential, but its performance is not automatically consistent across datasets and prediction conditions. The selection and optimization of the model therefore become important research issues.

The choice of input features also affects earthquake prediction substantially. Shrote et al. use latitude, longitude, and elevation to estimate earthquake magnitude and subsequently classify seismic risk [6]. Manral and Chaudhary use time, location, and previous seismic activity to predict earthquake magnitude and depth using Random Forest Regressor and Neural Network models [14]. Zhang et al. demonstrate that location and magnitude information can support regional earthquake early warning and achieve high classification accuracy after applying SMOTE to address data imbalance [10]. These studies indicate that geographic, temporal, and seismic variables provide useful predictive information. Nevertheless, excessive or weak features can introduce noise and reduce generalization. The study therefore needs an optimization strategy that identifies informative features and improves the relationship between input variables and the prediction model.

Model selection presents another important issue because different ML algorithms respond differently to earthquake datasets. Zhou and Che compare KNN, Naive Bayes, Random Forest, Logistic Regression, and SVM for seismic landslide susceptibility mapping. Their results show that Random Forest and SVM achieve the strongest performance, with AUC values approaching 1.0 [13]. Ghimire et al. also report that Random Forest provides the best regional seismic damage prediction among the evaluated methods [19]. Mir et al., however, show that model performance changes across experimental settings when predicting anomalies in radon time-series data. Their results identify SVM with a radial kernel and boosted tree as strong alternatives under different conditions [20]. These findings confirm that no single algorithm consistently dominates every earthquake-related dataset. An optimization method can help select or configure the most suitable model according to the characteristics of the available data.

Hyperparameter configuration further influences the effectiveness of earthquake ML models. Feroz et al. specifically investigates the impact of hyperparameter tuning on ensemble ML algorithms for earthquake damage prediction [5]. This issue becomes important because parameters such as tree depth, number of estimators, learning rate, kernel settings, and regularization directly affect model complexity and generalization. Joshi et al. develop an ensemble model for real-time earthquake magnitude prediction and combine real observations with CTGAN-generated synthetic data [4]. The approach addresses the difficulty of obtaining sufficient earthquake observations for model training. Yusof et al. similarly apply AutoML to automate algorithm selection and hyperparameter tuning using more than 50 years of geomagnetic observations. Their neural network achieves the best accuracy of 83.29% among five evaluated classifiers [11]. These studies indicate that systematic optimization can reduce manual trial-and-error and potentially improve earthquake prediction performance.

The temporal and real-time characteristics of earthquake prediction create additional challenges. Early warning systems must process incoming observations rapidly and produce predictions before strong ground motion reaches vulnerable locations. Zhang et al. develop a real-time seismic damage prediction framework that uses P-wave characteristics to directly estimate structural damage. Their framework achieves an average accuracy above 96.4% for risk-consistent early-warning trigger classification [15]. Chomchit and Champrasert combine CNN-based feature extraction with an Extreme Learning Machine to predict strong-motion earthquakes from initial P-wave signals. Their C-ELM model achieves prediction accuracy close to a conventional CNN while substantially reducing training time [21]. These results emphasize that prediction accuracy alone does not determine the usefulness of an earthquake prediction model. An effective approach must also provide efficient computation and rapid inference for practical warning applications.

Another challenge concerns the reliability and scalability of earthquake prediction systems. Wilk-Jakubowski et al. identify a growing integration of ML, IoT, image processing, and multi-sensor data fusion for real-time environmental hazard monitoring, including earthquakes [3]. Sanjay et al. propose a broader disaster management framework that combines seismic sensors, GPS stations, ocean buoys, satellites, and weather stations with ML and deep learning to support automated earthquake and tsunami warnings [2]. Such systems can provide richer information than a single sensor source, but they also introduce heterogeneous data, different sampling rates, missing observations, and varying levels of measurement uncertainty. Yusof et al. demonstrate that large-scale geomagnetic datasets can support automated model development, but they also acknowledge the difficulty of converting possible pre-earthquake anomalies into reliable practical predictions [11]. Therefore, optimization should consider not only predictive accuracy but also robustness, computational efficiency, and the ability to operate with diverse seismic observations.

Based on these issues, this study focuses on enhancing earthquake prediction using machine learning with an optimization method. Previous research establishes that ML can support earthquake magnitude prediction, seismic intensity estimation, ground-motion prediction, anomaly detection, and earthquake-related damage assessment [4], [10], [12], [15]. However, existing studies still report differences in model performance across datasets, features, algorithms, and experimental settings [7], [8], [13], [20]. This variation creates a clear opportunity to optimize the learning process rather than relying only on a conventional ML configuration. The proposed study therefore applies an optimization strategy to improve model selection and parameter configuration, reduce unnecessary prediction errors, and obtain a more reliable model. The main goal is to develop an earthquake prediction approach that balances accuracy, robustness, and computational efficiency for potential disaster early-warning applications [2], [3], [11], [21].

2. Related Works

Hassan investigated an SVM-based approach for earthquake detection using geophone data. The study focused on seismic signals recorded from geophones and applied SVM to identify earthquake-related patterns. This approach showed the potential of conventional machine learning to process seismic observations without relying on complex deep learning architectures. Its main strength was the use of direct sensor measurements for earthquake detection. However, the study focused primarily on detection rather than broader earthquake prediction. It also did not emphasize systematic optimization of SVM parameters or compare the optimized model with other machine learning configurations. These limitations indicated the need for an optimization strategy that could improve model performance and prediction reliability [1].

Sanjay et al. developed a disaster management system that combined machine learning and deep learning for earthquake and tsunami prediction. The system integrated data from seismic sensors, GPS stations, ocean buoys, satellites, and weather stations. The study showed that multi-source data could support automated detection, prediction, and early warning. Its major strength was the integration of heterogeneous real-time data within a disaster management framework. However, the study covered a broad disaster management scope and did not focus deeply on optimizing a specific prediction algorithm. The absence of detailed optimization analysis limited understanding of how parameter tuning could improve earthquake prediction performance [2].

Wilk-Jakubowski et al. reviewed the use of digital technologies, machine learning, IoT, and image processing for environmental hazard monitoring. The review showed that machine learning increasingly supported real-time monitoring and early warning for earthquakes and other hazards. It also emphasized multi-sensor data fusion and deep learning as important research directions. The study provided a broad view of current technological developments and highlighted the need for scalable and robust systems. However, it did not develop or experimentally validate a specific earthquake prediction model. It also did not examine optimization methods for improving the performance of individual machine learning algorithms [3].

Shrote et al. developed a machine learning approach for earthquake prediction using latitude, longitude, and elevation as input features. The predicted magnitude was then used to classify seismic risk into different categories. The study provided a clear prediction pipeline that included data collection, preprocessing, feature engineering, model construction, and evaluation. This approach showed that geographical features could contribute to earthquake risk estimation. However, the selected features provided only limited information about the complex temporal and seismic characteristics of earthquakes. The study also evaluated several machine learning methods without establishing a comprehensive optimization strategy for selecting model parameters and improving predictive performance [6].

Jarah et al. proposed a machine learning approach based on ground vibration measurements and sensor networks. The researchers used seismic records from Iraq and neighboring regions and divided the data into training and testing subsets. Their neural network model produced better seismic prediction results than the other evaluated methods. The study demonstrated the value of sensor-based seismic information and neural learning for earthquake prediction. However, the model relied on a conventional training configuration and did not provide an extensive investigation of hyperparameter optimization. This limitation suggested that further optimization could improve model accuracy and generalization across different seismic conditions [7].

Zhu et al. investigated machine learning for earthquake prediction using hydrochemical anomalies from six hot springs. The researchers developed a prediction model using six algorithms and analyzed events with magnitude $M \geq 5$ in Taiwan. Their results showed that machine learning performed better than traditional statistical approaches. They also found that including sampling time improved prediction performance. The study provided strong evidence that non-seismic environmental indicators could support earthquake prediction. However, prediction performance varied across monitoring sites and hydrochemical indicators. The model also could not clearly distinguish pre-earthquake anomalies from post-earthquake anomalies or determine the exact earthquake location. These limitations showed the importance of feature selection and model optimization [8].

Yusof et al. applied automated machine learning to geomagnetic field data for earthquake prediction. They used more than 50 years of observations from 131 magnetometer stations and extracted features using the wavelet scattering transform. The researchers applied automated algorithm selection and hyperparameter tuning using the asynchronous successive halving strategy. Their neural network model achieved the best performance, with an accuracy of 83.29%. The study demonstrated that automated optimization could reduce the manual effort required for model development. However, its performance remained moderate despite the extensive dataset and feature extraction process. The study therefore suggested that further optimization of features, model structures, and training parameters could improve earthquake prediction performance [11].

Mir et al. examined machine learning models for predicting anomalies in soil radon concentration associated with seismic activity. The study compared boosted tree, bagged CART, boosted linear models, SVM with linear and radial kernels, and KNN. The researchers found that SVM with a radial kernel performed well under several experimental settings, while boosted tree achieved the best results in another setting. The study demonstrated that algorithm selection strongly affected prediction performance. It also showed the importance of evaluating different model configurations under multiple time windows. However, the research predicted radon anomalies rather than earthquakes directly. The findings nevertheless supported the need to optimize machine learning algorithms and select suitable configurations for reliable earthquake-related prediction [20].

Zhang et al. developed a machine learning model for regional earthquake early warning using earthquake location and magnitude information. They addressed class imbalance using SMOTE and constructed separate models for different magnitude ranges. The model achieved 97.77% accuracy under specified magnitude and location errors. This study demonstrated the effectiveness of pre-processing and model design in improving earthquake warning performance. However, the model focused on seismic intensity estimation rather than direct earthquake occurrence prediction. Its performance also depended on location and magnitude information that may contain measurement errors. These limitations highlighted the need for an optimization framework that jointly considers data characteristics, model parameters, and prediction reliability [10].

Previous studies showed that machine learning provided strong potential for earthquake detection, prediction, intensity estimation, and seismic damage assessment. However, many studies focused on a specific data source or prediction task, while fewer studies systematically optimized the complete prediction process. SVM, neural networks, random forests, ensemble models, and automated machine learning methods showed different strengths under different data conditions [1], [7], [10], [11], [20]. The findings also showed that pre-processing, feature selection, class balancing, hyperparameter tuning, and algorithm selection directly affected model performance [8], [10], [11]. Therefore, an optimized machine learning approach can address an important research gap by combining suitable seismic features with systematic parameter optimization. This approach can improve prediction accuracy while maintaining a practical and computationally efficient earthquake prediction system.

3. Proposed Method

The proposed method consists of six main stages: data collection, data pre-processing, feature selection, dataset division, model building, and model evaluation. First, we collect earthquake data from official BMKG sources. We then pre-process the data by selecting earthquake events with a magnitude of ≥4 and shallow depth and converting categorical or string-based values into numeric formats. Next, we select the most relevant features to reduce model complexity and improve prediction efficiency. We divide the dataset using K-Fold Cross-Validation to obtain a fair and reliable evaluation across different data subsets. We evaluate the model using the F1-Score to measure its ability to correctly classify earthquake events while balancing precision and recall.

This study proposes a machine learning approach to enhance earthquake prediction using Random Forest with an optimization process. The proposed method consists of six stages: data collection, pre-processing, feature selection, and dataset splitting. We collect earthquake records from official BMKG sources and select relevant seismic attributes, such as magnitude, depth, latitude, longitude, and other available parameters. We pre-process the dataset by converting non-numeric attributes into numerical values and removing incomplete or irrelevant records. We then define the earthquake prediction class based on the study criteria. Feature selection is applied to retain the most informative variables and reduce model complexity. This paper uses K-Fold Cross-Validation to obtain a reliable estimate of model performance. We apply Random Forest because it can capture nonlinear relationships and reduce the overfitting risk associated with a single decision tree.

Random Forest constructs an ensemble of T decision trees from bootstrap samples of the training dataset. For each tree t, the model can be expressed as:

$$h_t(x) = \text{DecisionTree}_t(x), t = 1,2, \dots, T$$

where x represents the input earthquake features and $h_t(x)$ represents the prediction generated by the t-th decision tree.
For classification, Random Forest determines the final class using majority voting:

$$\hat{y} = \mathrm{argmax}_c \sum_{t=1}^{T} I(h_t(x) = c) \quad (1)$$

where $\hat{y}$ is the final predicted earthquake class, c represents a possible class, T is the number of decision trees, and $I(\cdot)$ is an indicator function that returns 1 when the tree prediction belongs to class c and 0 otherwise. Thus, the class receiving the largest number of votes becomes the final prediction.
At each node, the decision tree selects a feature and split that maximizes the reduction in impurity. We use Gini impurity, defined as:

$$G = 1 - \sum_{c=1}^{C} p_c^2 \quad (2)$$

where C is the number of classes and p_c is the proportion of samples belonging to class c. A lower Gini value indicates a purer node. The Random Forest algorithm repeatedly selects splits that reduce this impurity and produces multiple diverse trees.

This study optimizes the main Random Forest hyperparameters, such as the number of trees, maximum tree depth, minimum samples required for splitting, and the number of features considered at each split. The optimization objective can be formulated as:

$$\theta^* = \mathrm{argmax}_\theta F1(\theta) \quad (3)$$

where θ represents the Random Forest hyperparameter configuration and θ^* represents the optimal configuration. The F1-Score is calculated as:

$$F1 = 2\frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

where Precision measures the proportion of predicted earthquake events that are correct, while Recall measures the proportion of actual earthquake events that the model successfully identifies. The F1-Score provides a balanced evaluation between these two measures, making it appropriate when the earthquake classes are imbalanced.

4. Experimental Setup

In this study, we gathered the dataset through a data retrieval process from the official website of BMKG Indonesia. This dataset consists of 77,257 entries that include parameters such as date, time, latitude, longitude, depth, magnitude, tsunami potential, and region. Table 1 displays training and testing dataset.

Table 1. Training and Testing Dataset

Dataset	Percentage	Number of Records
Training Data	80%	61,806
Testing Data	20%	15,451
Total	100%	77,257

In this study, we divided into 80% training data and 20% testing data. The training set consisted of 61,806 records. The remaining 15,451 records were used to evaluate the model's performance on previously unseen data.

5. Result and Analysis

In this study, the K-Means clustering algorithm is applied to group earthquake records according to their seismic characteristics. The clustering process uses numerical attributes such as latitude, longitude, magnitude, and depth. The value of K=3K=3 is used to produce three clusters, which are interpreted as Dangerous, Medium, and Not Dangerous. Table 2 displays K-Means Clustering results.

Table 2. K-Means Clustering Results

No.	Date	Time	Latitude	Longitude	Magnitude	Depth	Location	K-Means Cluster
1	2022/03/30	18:00:57	1.77	-7.65	6.7	400 km	Maluku	Dangerous
2	2022/03/29	06:15:41	-2.56	1.89	3.2	186 km	Sulsel	Not Dangerous
3	2022/03/28	12:23:31	-1.78	-15.22	4.6	386 km	Sumbar	Medium
4	2022/03/27	14:45:47	0.77	-7.65	6.4	89 km	Maluku	Dangerous

The clustering results provide a simplified classification of earthquake observations based on their similarity. In the sample data, the earthquakes with magnitudes 6.7 and 6.4 are assigned to the Dangerous cluster, the magnitude 4.6 earthquake is assigned to the Medium cluster, and the magnitude 3.2 earthquake is assigned to the Not Dangerous cluster. The cluster labels should be understood as the interpretation of the K-Means output rather than as directly observed BMKG labels.

Table 3. F1-Score Comparison of Machine Learning Models

Machine Learning Model	Number of Trees	F1-Score (%)
Random Forest	50	82.53
Random Forest	60	83.32
Random Forest	70	82.24
Random Forest	80	84.48
Random Forest	90	85.39
Random Forest	100	87.21
Naïve Bayes	–	85.89
Decision Tree	–	86.24
SVM	–	87.11

The results show that the Random Forest model achieves progressively better F1-Score as the number of trees increases, although a slight decrease occurs at 70 trees. The highest Random Forest performance is obtained with 100 trees, achieving an F1-Score of 87.21%. This result slightly exceeds the SVM model at 87.11% and the Decision Tree model at 86.24%, while Naïve Bayes achieves 85.89%.

Table 4. F1-Score Based on Feature Combinations

No.	Feature Combination	F1-Score (%)
1	Date, Latitude, Longitude, Magnitude, Location	93.23
2	Date, Latitude, Longitude, Magnitude, Depth	91.44
3	Latitude, Longitude, Magnitude, Location	90.12
4	Latitude, Longitude, Magnitude, Tsunami, Location	89.78
5	Date, Time, Latitude, Longitude, Magnitude, Tsunami, Location	87.21
6	Latitude, Longitude, Magnitude, Tsunami, Location	86.95

The feature analysis demonstrates that the combination of Date, Latitude, Longitude, Magnitude, and Location produces the highest F1-Score of 93.23%, indicating that these features provide the most effective information for the classification task. The combination of Date, Latitude, Longitude, Magnitude, and Depth achieves the second-highest performance at 91.44%, while removing Date reduces the F1-Score to 90.12%. The inclusion of Tsunami-related information does not improve performance in the evaluated combinations, with F1-Scores ranging from 86.95% to 89.78%. Interestingly, adding Time to the feature set results in an F1-Score of 87.21%, suggesting that Time may introduce less useful information or additional variability. The results indicate that Date, geographic coordinates, Magnitude, and Location are the most influential features for achieving strong classification performance.

6. Conclusion

This study demonstrates that we can utilize K-Means clustering to group earthquake records based on their seismic characteristics. We use latitude, longitude, magnitude, and depth to identify three clusters. We interpret these clusters as Dangerous, Medium, and Not Dangerous based on their characteristics. The clustering results provide a simplified representation of earthquake conditions and can generate additional labels for subsequent prediction analysis. However, these labels represent the K-Means interpretation and do not directly represent observed BMKG classifications.

This paper applies Random Forest and compares its performance with Naïve Bayes, Decision Tree, and SVM. We evaluate different numbers of trees in the Random Forest model. The results show that 100 trees provide the highest Random Forest performance, with an F1-Score of 87.21%. This result slightly exceeds SVM at 87.11%, Decision Tree at 86.24%, and Naïve Bayes at 85.89%. Therefore, we use Random Forest with 100 trees as the best configuration among the evaluated models. The result also indicates that increasing the number of trees can improve performance, although the improvement is not always consistent.

The feature analysis further shows that feature selection strongly affects the prediction performance. We utilize Date, Latitude, Longitude, Magnitude, and Location as the most effective feature combination, which produces the highest F1-Score of 93.23%. This result improves the Random Forest performance from 87.21% to 93.23%. The combination of Date, Latitude, Longitude, Magnitude, and Depth also performs well with an F1-Score of 91.44%. In contrast, adding Time and Tsunami information does not improve the model in the evaluated combinations. Overall, this study shows that combining K-Means clustering, appropriate feature selection, and Random Forest can enhance earthquake classification performance.

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