ISSN: 2579-5821 (Print)
ISSN: 2579-5546 (Online)
URL address: http://journal.unhas.ac.id/index.php/geocelebes
DOI: 10.70561/geocelebes.v10i1.42958

Jurnal Geocelebes Vol. 10 No. 1, April 2026, 1 – 11

The Earthquake Prediction in the Southern Part of Sumatra Using Deep Learning (Long Short-Term Memory) Models

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Manuscript received: 20 January 2025; Received in revised form: 4 February 2025; Accepted: 5 February 2025

Abstract

The Southern part of Sumatra is highly vulnerable to earthquakes due to its location in the subduction zone between the Indo-Australian plate and the Sunda plate. The Southern part of Sumatra's vulnerability to earthquakes poses significant risks. This research aims at predicting the Earthquakes in the Southern part of Sumatra Using Deep Learning (Long Short-Term Memory) Models, a deep learning method designed to analyze sequential data. The model utilized 20 years of historical earthquake data from 2004 to 2024, with parameters including magnitude, epicenter location, depth, and event time. Data were preprocessed using Min-Max Scaling normalization and split into training data (70%) and testing data (30%). The model was trained over 150 epochs with a batch size of 32. Evaluation results showed a Mean Absolute Error (MAE) of 0.28 and a Root Mean Squared Error (RMSE) of 0.39, indicating high prediction accuracy. The distribution of prediction results confirmed previous studies indicating that earthquakes in Southern part of Sumatra frequently occur in Bengkulu, western South Sumatra, and Southwestern Lampung. These findings underscore the importance of ongoing seismic hazard mitigation efforts and sustainable development planning in earthquake-prone areas.

Keywords: Earthquake; Historical Data; LSTM; Southern part of Sumatra.

Citation: Lisa, A., Refrizon, R., & Samdara, R. (2026). The Earthquake Prediction in the Southern Part of Sumatra Using Deep Learning (Long Short-Term Memory) Models. *Jurnal Geocelebes*, 10(1): 1–11, doi: 10.70561/geocelebes.v10i1.42958

Introduction

The Southern part of Sumatra, encompassing South Sumatra, Lampung, Jambi, and Bengkulu, plays a strategic role in supporting national development. This region is known for its abundant natural resources, including mining products, oil, gas, and plantations. Additionally, the presence of major infrastructure such as the Trans-Sumatra Highway, key ports, and ambitious projects like the Trans-Sumatra Toll Road has positioned this region as a growing economic hub (Al-Faridzi & Kurniasari, 2024).

However, alongside its economic potential, Southern part of Sumatra faces significant challenges, primarily in the form of earthquake risks. This area lies in an active subduction zone, where the Indo-Australian and Sunda plates converge, recognized as one of the most seismically active zones globally (Sukrungsri et al., 2024). Furthermore, the Sumatra Fault, which extends longitudinally from the island's north to south, exacerbates the risk of tectonic earthquakes. Historical records highlight major earthquakes, such as the 2007 Bengkulu earthquake with a magnitude of 8.4 (Mase, 2021), which caused extensive damage, and the 2010 Mentawai earthquake (Marzuki et al., 2022), which triggered a tsunami. These vulnerabilities necessitate special attention, particularly in disaster mitigation efforts.

Ongoing development in the region increases the risks associated with earthquakes, potentially leading to significant material and non-material losses. Damaged infrastructure, disrupted economic activities, and widespread social impacts are some of the serious consequences that need to be anticipated. Furthermore, the region has experienced a significant population increase, particularly in earthquake-prone areas, amplifying the potential for disaster-related losses. Damage to vital facilities such as roads, bridges, and healthcare centers can impede evacuation processes and emergency responses, ultimately worsening the disaster's impact on communities (Yang et al., 2024).

In addition to these issues, the potential disruption of economic activities must also be considered. Southern part of Sumatra, which serves as a center for resource-based economic activities such as plantations, mining, and logistical transportation, heavily relies on robust and operational infrastructure. Without adequate mitigation measures, earthquake-induced damage could hinder the distribution of goods, trade activities, and regional economic stability (Samudra et al., 2024). Therefore, disaster mitigation must be comprehensively designed, encompassing infrastructure strengthening, region-based risk management, and spatial planning that considers earthquake risks. This approach should not only be reactive but also proactive, aiming to minimize future losses, one of which is through more accurate earthquake predictions.

Advancements in technology in the modern era provide significant opportunities for disaster risk management. Artificial intelligence-based technologies, such as Long Short-Term Memory (LSTM), offer innovative solutions to predict earthquake patterns using historical data (Mer et al., 2024). LSTM is a deep learning method designed to analyze sequential data while retaining relevant temporal information. Previous research has demonstrated this method's effectiveness in predicting time-based events, particularly for problems involving long-term patterns (Lin et al., 2024).

This study aims to develop an LSTM-based earthquake prediction model using historical earthquake data from Southern part of Sumatra over the past two decades. By considering parameters such as magnitude, depth, epicenter location, and event time, this research is expected to provide more accurate prediction results. These findings are hoped to support disaster mitigation efforts, strengthen resilient development planning, and enhance community preparedness against potential future earthquakes.

Artificial intelligence-based technologies, such as LSTM, offer innovative solutions to predict earthquake patterns using historical data (Mer et al., 2024). Several studies have shown that LSTM can effectively capture spatial and temporal patterns in seismic records, making it a valuable tool for earthquake forecasting.

For instance, Sonthalia et al. (2023) developed an LSTM-based model capable of predicting earthquake magnitude occurrences with higher accuracy compared to traditional statistical methods. Similarly, Kavianpour et al. (2024) introduced a hybrid CNN-BiLSTM model with an attention mechanism, which significantly enhanced the accuracy of magnitude predictions. Additionally, Berhich et al. (2020) applied LSTM to spatiotemporal earthquake data, demonstrating that the model performed well in forecasting both earthquake locations and magnitudes. These findings underscore the increasing role of deep learning, particularly LSTM, in improving the effectiveness of earthquake prediction models. Therefore, in this study, the LSTM method is applied to develop an earthquake prediction model for the Southern part of Sumatra.

Long Short-Term Memory (LSTM)

Deep Learning is a branch of Artificial Intelligence (AI) that focuses on the use of artificial neural networks with multiple layers to process data (Nurhakiki & Yahfizham, 2024). One of the popular models for sequential data applications is LSTM, a type of Recurrent Neural Network (RNN) designed to retain information over long periods (Adherda et al., 2023). LSTM is particularly useful in analyzing time-series data containing temporal patterns, such as seismic data related to earthquakes.

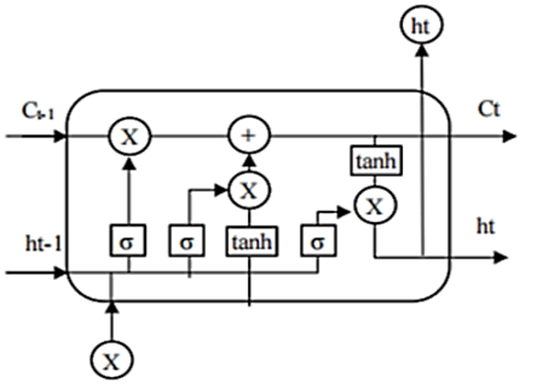

Figure 1. LSTM Architecture (Sianturi et al., 2023).

LSTM has the capability to learn from more than 1000 previous time steps (Verianto, 2024), depending on the complexity of the network. The core concept of LSTM lies in the Cell State, which is controlled by a gating mechanism within a single LSTM unit and passed on to the next unit through the following main gates: Forget Gate, Input Gate, and Output Gate (Fig. 1).

Materials and Methods

The steps involved in this research are illustrated in Fig. 2, which presents the research framework. The explanation of each step is as follows:

1. Load Data

The data loaded into the system consisted of historical earthquake records from the Southern part of Sumatra region spanning the years 2004 to 2024. The data were sourced from the official IRIS Wilber 3 website, with constraints set for magnitudes ranging from 5 to 10 and depths between 10 and 60 km.

2. Pre-Processing Data

a) Resampling Data

The earthquake data spans a 20-year period with varying time intervals, requiring resampling techniques to adjust the recording frequency. Resampling ensured that the data intervals were consistent and met the requirements of the LSTM model, which is sensitive to temporal irregularities. For instance, earthquake recordings may not have been conducted uniformly on a daily basis. Through resampling, the data was transformed into fixed intervals, such as daily or monthly, making temporal patterns easier to identify and analyze by the LSTM. Additionally, methods like down-sampling were employed to simplify the data by removing redundant information that was irrelevant to the main patterns, thereby enhancing the model's efficiency (Gerlach et al., 2024).

b) Data Normalization

Normalization was performed to prevent issues during model training due to scale discrepancies among features. A commonly used technique is Min-Max Scaling, which transforms data values into a range of 0 to 1 (Ma, 2024). In the LSTM model, normalization was applied prior to data utilization to ensure that all features were within a consistent scale, thus preventing the dominance of specific features. After predictions were generated, denormalization was applied to facilitate easier interpretation of the results.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

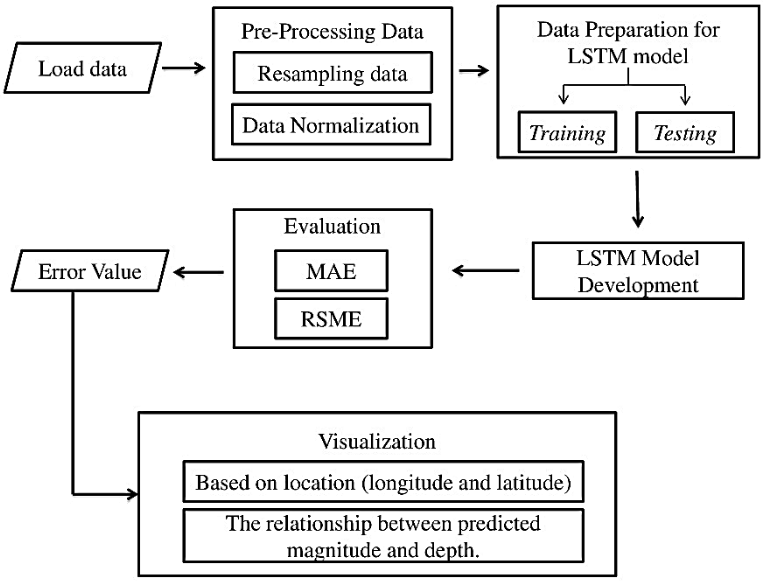

Figure 2. Research methodology diagram.

3. Data Preparation

Before being input into the LSTM model, the data were prepared in a format suitable for time-series input. The dataset was divided into training data (70%) and testing data (30%).

4. LSTM Model Development

Traditional Recurrent Neural Networks (RNN) often suffer from the vanishing gradient problem, limiting their effectiveness in processing long sequences. According to Bellamkonda et al. (2021), LSTM mitigates this issue by employing memory cells and gating mechanisms, enabling it to retain significant patterns in seismic activity over extended periods. This capability allows LSTM to establish complex temporal relationships within earthquake datasets, making it a more suitable choice compared to conventional RNN and Feedforward Neural Networks (FNN).

To standardize data distributions and facilitate stable training, Min-Max Scaling was applied to normalize input values, ensuring that all features operated within a consistent numerical range. By integrating these preprocessing techniques, the model aimed to optimize earthquake prediction accuracy and mitigate overfitting issues associated with deep learning models.

5. Evaluation

The model was trained over 150 epochs with a batch size of 32 samples per iteration. Testing was conducted using the testing dataset. The evaluation metrics used were MAE and RMSE. Low error values indicated the effectiveness of the developed model.

a) Mean Absolute Error (MAE)

MAE calculates the average absolute difference between predicted values (y-pred) and actual values (y-true), indicating the magnitude of the model's average error without considering the direction of the error. The formula is (Scott & Willmott, 2023):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{pred,i} - y_{true,i}\right| \qquad (2)$$

where:

- n is the number of data points
- $y_{pred,i}$ is the predicted value for the i-th data point
- $y_{true,i}$ is the actual value for the i-th data point

b) Root Mean Squared Error (RMSE)

RMSE is the square root of the average squared differences between predicted values (y-pred) and actual values (y-true). This metric measures the average error while giving greater weight to larger errors compared to MAE. Some characteristics of RMSE include: its scale being the same as the original data, a significant influence of large errors due to the squaring process, and higher sensitivity to outliers compared to MAE. The formula is (Hodson, 2022):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{pred,i} - y_{true,i})^2} \quad (3)$$

6. Visualization

The final stage involved visualizing the earthquake prediction results. The first visualization, based on location (longitude and latitude), was implemented using libraries such as Matplotlib or Folium. The second visualization, a graphical representation, was used to analyze the relationship between predicted magnitude and depth.

Results and Discussion

All data loaded into the system were formatted using a datetime structure, as shown in Table 1, before undergoing the data preprocessing stage.

Table 1. Historical earthquake data with datetime format.

Date	Latitude	Longitude	Depth	Magnitude
8-2-2004	-5.4608	102.6564	42.800	5.5
10-24-2004	-4.8658	101.8926	28.100	5.3
10-28-2004	-4.9375	103.2393	41.500	5.3
10-28-2004	-4.9000	103.2507	58.100	5.0
12-26-2004	-3.3512	101.6312	53.000	5.0
…	…	…	…	…
10-29-2023	-4.3162	102.0295	58.539	5.1
2-5-2024	-2.1520	100.4749	51.246	5.0
3-4-2024	-5.7671	102.2524	10.000	5.2
6-5-2024	-3.5277	100.7812	30.666	5.0

Table 2. Results of normalization or scaling.

Latitude	Longitude	Depth	Magnitude
0.142	0.095	0.627	0.658
0.085	0.200	0.461	0.363
0.085	0.187	0.754	0.632
0.000	0.194	0.757	0.965
0.000	0.468	0.404	0.862

Next, the data were normalized to ensure that all features contributed equally during the training process. This step mapped data with initially varying ranges into a uniform scale between 0 and 1. Examples of normalized data for features such as magnitude, latitude, longitude, and depth are presented in Table 2.

Subsequently, sequential data were prepared by utilizing the previous 30 data points to predict target values. The data were then split into training and testing sets, allowing input into the LSTM multiple-output sequential model. The model, detailed in Table 3, consists of LSTM layers for extracting temporal patterns from sequential data, dropout layers to mitigate overfitting, and dense layers for generating four output values. The evaluation results, summarized in Table 4, indicate small error values, demonstrating the strong performance of the earthquake prediction model.

Table 3. LSTM model.

Layer (type)	Output Shape	Params
LSTM	(None, 50)	11
Dropout	(None, 50)	0
Dense	(None, 4)	0.204

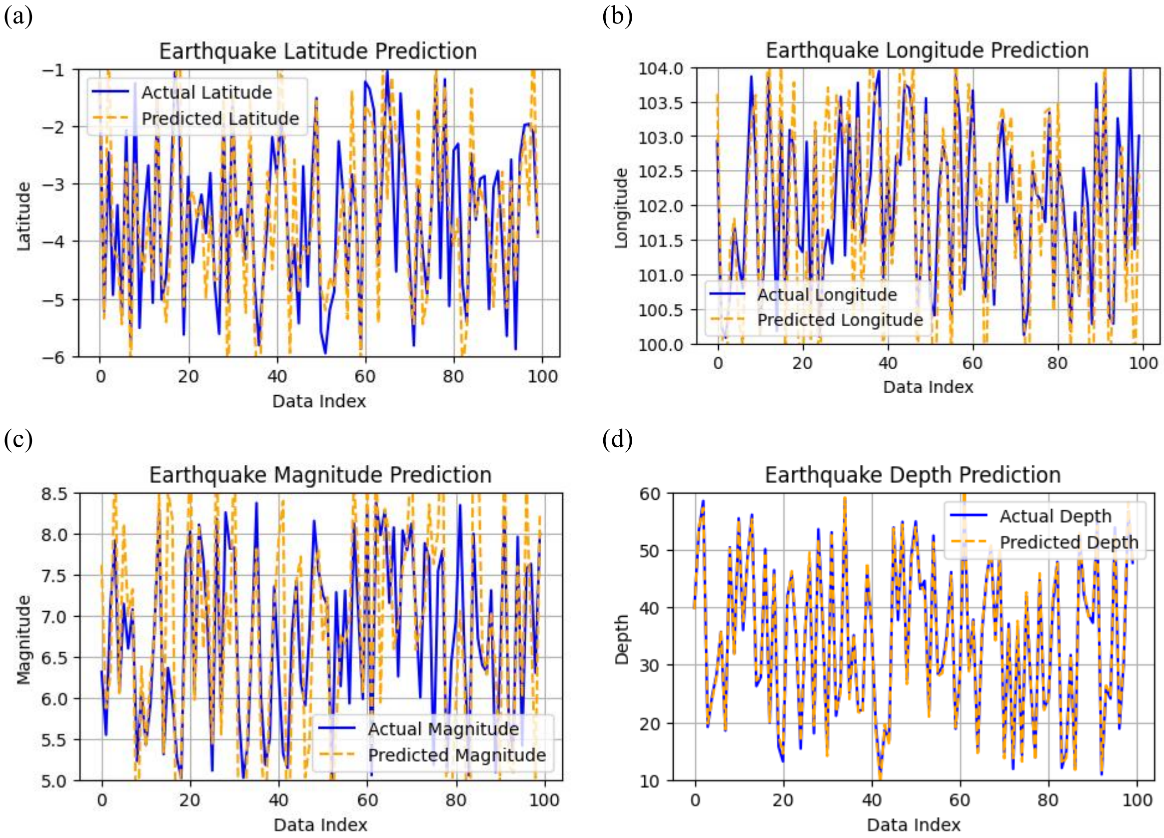

Figure 3. Comparison curve between actual data and prediction results: (a) Earthquake latitude prediction, (b) Earthquake longitude prediction, (c) Earthquake magnitude prediction, (d) Earthquake depth prediction.

Table 4. Error metrics.

Metrics	**Predicted Values**
MAE	0.283
MSE	0.156
RMSE	0.395

The model contains a total params: 11.204 (43.77 KB), trainable params: 11.204 (43.77 KB), non-trainable params: 0 (0.00 KB).

Fig. 3 illustrates the earthquake prediction curve generated by the LSTM model. It compares predicted values with actual values based on parameters such as magnitude, latitude, longitude, and depth. Additionally, two plots were generated from this curve to analyze the distribution of predicted earthquakes. The first plot (Fig. 4) shows the distribution based on latitude and longitude, while the second plot (Fig. 5) focuses on the distribution based on magnitude and depth.

Fig. 3 illustrates the comparison between actual values (solid blue line) and predicted results (dotted orange line) generated by the prediction model. From the graph, it can be observed that the prediction pattern closely resembles the actual data. This visualization demonstrates that the gap between the predicted and actual lines is relatively small for most data points.

This indicates that the model performs well in predicting earthquakes. The MAE and RMSE error values presented in Table 4 are also low, further confirming that the LSTM model can produce predictions with minimal errors, thereby validating the model's effectiveness in capturing patterns in historical data.

The earthquake prediction modeling results indicated that earthquakes frequently occurred in the Southern part of Sumatra region with magnitudes ranging from 5.0 to 6.0 and depths between 20 and 60 km. Based on Fig. 4, the coordinates revealed that earthquakes commonly occurred at latitudes between -2° and -6°, representing areas south of the equator, and longitudes between 100°E and 104°E, encompassing the western part of Sumatra. Most of these earthquake occurrences were concentrated in the Southern part of Sumatra region, including Bengkulu Province, western South Sumatra, and southwestern Lampung. This area is part of an active subduction zone, making it highly prone to seismic activity. Furthermore, high-magnitude earthquakes (7.0–8.5) at depths between 20 and 37 km were found to occur near the western coastline of Sumatra Island, specifically within coordinates of longitudes 100°–102° and latitudes -2° to -5°. This region forms part of the megathrust zone along the convergence boundary of the Indo-Australian and Sunda plates (Azmiyati, 2021).

These findings align with the geological characteristics of Sumatra, which is dominated by the subduction of the Indo-Australian plate beneath the Sunda plate, resulting in frequent seismic activities. The zone along the western coastline, extending from Aceh in the north to Lampung in the south, is known to generate significant earthquakes with the potential for triggering tsunamis. This makes the region a critical area for disaster preparedness and mitigation efforts (Firmansyah et al., 2022).

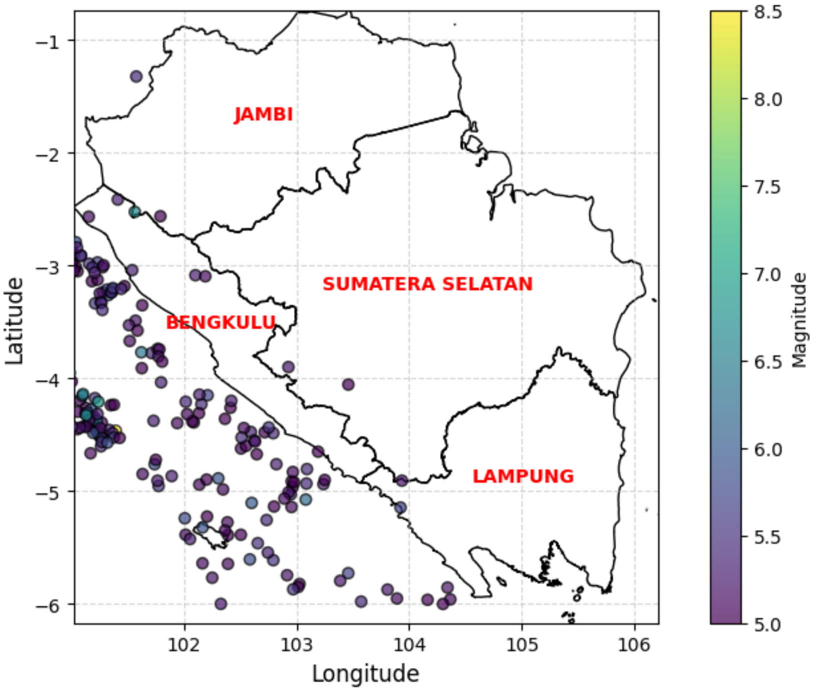

Figure 4. Earthquake distribution based on longitude and latitude.

The earthquake prediction model also highlighted patterns in the temporal distribution of seismic events. Most earthquakes occurred during specific periods, indicating potential seasonal or temporal trends influenced by tectonic stress accumulation and release in the subduction zone. These temporal patterns can be further studied to enhance the predictive accuracy of seismic models and improve early warning systems for high-risk areas.

Additionally, the results emphasized the importance of region-specific mitigation strategies, particularly in densely populated and economically vital areas like Bengkulu, South Sumatra, and Lampung. Infrastructure in these regions, including transportation networks, industrial facilities, and residential areas, must be designed and retrofitted to withstand seismic impacts. The study also underscores the potential of advanced machine learning models, such as LSTM, in contributing to disaster risk management. By incorporating historical seismic data and leveraging the model's capability to identify long-term dependencies, LSTM-based predictions offer valuable insights for policymakers, urban planners, and disaster management agencies. These predictions can support the development of targeted risk reduction measures, such as optimized evacuation plans, improved land-use planning, and enhanced public awareness campaigns.

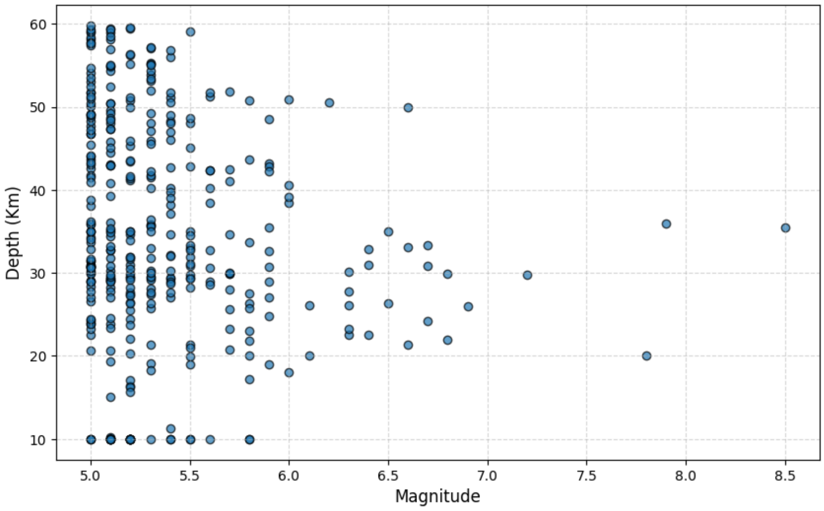

Figure 5. Earthquake distribution based on magnitude and depth.

Future research could further refine the model by integrating additional parameters, such as soil type, fault activity, and energy distribution during seismic events, to improve prediction accuracy. Moreover, the inclusion of real-time seismic monitoring data and the expansion of the dataset to include other regions in Indonesia could make the model more robust and broadly applicable. This would support a more comprehensive approach to earthquake disaster mitigation across the archipelago, ultimately reducing the social and economic impacts of seismic events.

Conclusion

This study successfully developed an LSTM-based earthquake prediction model using historical data from Southern Sumatra (2004–2024). The model demonstrated reliable performance in predicting earthquake parameters, with a MAE of 0.28 and RMSE of 0.39, indicating good accuracy. High-risk areas were identified around Bengkulu, western South Sumatra, and southwestern Lampung, with most predicted earthquakes ranging from magnitudes 5.0–6.0 at depths of 20–60 km, aligning with active subduction zone characteristics.

These findings contribute to disaster mitigation by aiding government and stakeholders in preparedness and infrastructure planning. Future enhancements could integrate real-time data, such as satellite and GPS observations, to improve accuracy. This model offers a scalable framework for earthquake prediction in other seismically active regions, supporting global disaster risk reduction.

Acknowledgements

The authors would like to express their heartfelt gratitude to the editors, reviewers, and proofreaders for their constructive feedback and assistance in refining this manuscript.

Special thanks are extended to the technical staff and colleagues at the Physics and Geophysics Departments, Faculty of Mathematics and Natural Sciences, Universitas Bengkulu, for their support in equipment preparation and data analysis. The authors also acknowledge those who contributed to the survey and data collection, which were essential for developing the Long Short-Term Memory (LSTM) models for earthquake prediction in Southern part of Sumatra.

Author Contribution

Ainul Lisa: Conceptualization, Methodology, Data Analysis, Writing – Original Draft. **Refrizon**: Supervision, Validation, Writing – Review & Editing. **Rida Samdara**: Data Collection, Resources, Visualization.

Conflict of Interest

The authors declare that they have no conflict of interest. There are no financial or personal relationships with any individuals or organizations that could inappropriately influence (bias) the work presented in this study.

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