

Application of First-Order Markov Chain Models in Earthquake Activity Prediction

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Abstract—Indonesia is situated between three different tectonic plates, making it one of the most seismically active areas. Providing exact prediction to when and where earthquake may happen remains challenging due to its unpredictability, varied factors and complex seismic processes. This study proposes a probabilistic framework that predicts earthquake activities using a first-order Markov Chain model. Historical earthquake data from Badan Meteorologi, Klimatologi, dan Geofisika (BMKG) and The United States Geological Survey (USGS) data were preprocessed and converted into discrete seismic events. States are defined based on earthquake magnitude, depth, and geographic location. The model creates a matrix that shows the probabilities of moving from one state to another to estimate future seismic activity patterns over time. Experimental Results show that the proposed approach works well in capturing short-term seismic transition behavior, including regional persistence and magnitude continuity. Top-1 and Top-3 prediction accuracies of 21.00% and 39.53% represents the improvements that are each 26.67 times and 16.74 times better than the baseline. This demonstrates that the model learns significant patterns across 127 possible states. The framework provides interpretable probabilistic forecasts with low computational efficiency, making it a lightweight baseline for analyzing earthquake sequences and combining them into data-driven approaches for disaster mitigation uses.

Index Terms—Earthquake prediction, Markov chain, Probabilistic forecasting, Seismic hazard, Transition probability matrix, Disaster mitigation, Indonesia.

I. INTRODUCTION

Indonesia ranks among the most seismically hazardous regions in the world, located near the convergence of major tectonic plates that generates near-continuous earthquake activity with severe consequences for infrastructure, public safety, and economic stability [1]. However to predict such events involves studying processes in geophysical science like earthquakes, which naturally behave in a nonlinearly and stochastic in nature. This rendering deterministic approach are often fundamentally inadequate [2], [3].

Recently, researches uses data-driven and probabilistic methods to study earthquakes patterns. They demonstrated strong performance across seismic detection, phase picking, and pattern recognition tasks [4], [5], [6]. Although deep learning has performed well in detecting seismic activity and recognizing patterns, these models require a number of labeled data, need significant computing power resources, and

have results which are complex to interpret, which is highly unadvisable for urgent early warning systems [7], [8], [9].

Markov Chain models has been proven to performed well for analyzing sequential events such as seismic activity [10], [11]. This development occurs given that they focus on how one state changes into another. Markov models are highly effective at capturing the sequential dependencies and stochastic transitions of geophysical events, existing literature often limits the scope of state definitions by strictly using earthquake magnitude.

As such this study suggests to expands the framework in using factors like geographical area, depth and magnitude of each earthquake by using catalog data provided publicly by BMKG and USGS. The model will use a first order Markov Chain to calculate transition probabilities between multi-dimensional seismic states.

The subsequent sections of this manuscript are arranged as follows: Section II evaluates existing literature regarding stochastic modeling and limitations in current seismic forecasting. Section III outlines the framework, dataset preparation, and the criteria used for state definitions. Section IV presents the empirical transition matrix findings and discusses model performance metrics. Finally, Section V concludes with operational deployment insights for early warning systems and outlines avenues for future research.

II. LITERATURE REVIEW

Existing literature often employs Markov Chain models as a proven probabilistic framework for analyzing discrete stochastic systems. Gulia and Wiemer [12] demonstrated that real-time probabilistic analysis enables discrimination between foreshock and aftershock sequences. On the other hand, Console et al. [13] reported measurable probability gains over deterministic reference models. Spassiani and Sebastiani [14] further showed that magnitude-dependent stochastic models can characterize aftershock sequences with interpretable physical parameters. However, these Markov-based models limit the state spaces to earthquake magnitude alone [10], [11]. These approaches overlook spatial variables such as depth and geographic distribution, consequently omitting fundamental drivers of seismic migration patterns.

This first order formulation of the model uses a mathematically tractable method for recognizing earthquake sequence behavior by relying on the Markov property which dictates that transition to a future seismic state is conditioned solely on the present observation, thereby minimizing parameter demands while preserving model transparency [15]. Despite the fact that higher order methods can theoretically handle longer temporal dependencies, they require more parameters and carry greater overfitting risk [16], [17]. This risk is further heightened by the uneven distribution of Indonesia's seismic records.

Parallel to these stochastic methods, deep learning architectures have driven substantial progress across solid Earth geoscience, demonstrating capabilities that range from the automated discovery of macro-geophysical patterns [5] and the effective denoising of complex seismic signals [18], to mapping high-dimensional spatial aftershock distributions directly from stress change inputs [6]. Despite these advances, deep learning models consistently require large annotated datasets, substantial hardware, and offer limited output transparency.

From the literature above, several gaps can be noted that concern this study. First, conventional Markov-based seismic models exhibit dimensional constraints, that is, by limiting their state space definitions strictly to earthquake magnitude. Second, there is a lack of standardized benchmarking in stochastic forecasting frameworks, which are rarely evaluated against quantitative baseline metrics. Lastly, advanced alternative methodologies often introduce severe interpretability and computational load, restricting practical deployment as early warning tools. This study addresses these limitations by using a multidimensional Markov framework that incorporates spatial and depth variables while maintaining the computational efficiency and structural transparency required for operational forecasting.

III. RESEARCH METHODOLOGY

A. Markov Chain Framework and Research Design

This study adopts a quantitative approach to model regional earthquake activity in Indonesia through a discrete stochastic process. A first-order Markov Chain is utilized to capture how seismic states transition into one another over time. Historical earthquake sequences are aggregated into discrete monthly intervals as opposed to evaluating continuous variables. Each interval represents a unique multi-dimensional seismic state determined concurrently by earthquake magnitude, focal depth, and geographic region.

Through the Markov property, the model assumes that the next seismic state is conditioned exclusively upon the present state observation. Transition frequencies are calculated from historical seismic records and mathematically converted into a normalized transition probability matrix. The resulting matrix yields highly interpretable and computationally efficient probability distributions of future seismic activity levels to enhance regional disaster preparedness. This framework operates as a low-cost probabilistic inference module designed for

integration into sensor-driven Early Warning System (EWS) platforms.

B. Dataset Description

The dataset was obtained from BMKG and USGS earthquake records accessed through Kaggle. Each record of earthquakes includes event time, magnitude, depth, latitude, and longitude. The dataset spans multiple years and contains tens of thousands of earthquake events. To support Markov Chain modeling, earthquake events were aggregated into monthly intervals. Several preprocessing steps were performed, including removing missing values, filtering unrealistic depth and magnitude values, and converting continuous earthquake attributes into discrete seismic states. The dataset is then partitioned chronologically, with 80% allocated for training and the remaining 20% reserved for evaluation.

C. Earthquake Depth and Region State Definition

Continuous geographic and structural values are transformed according to the thresholds defined in Table I.

TABLE I
EARTHQUAKE DEPTH AND REGION STATE DEFINITION

Attribute	State Label	Range
Depth (km)	Shallow	< 70 km
	Intermediate	70–300 km
	Deep	> 300 km
Region (Latitude / Longitude)	Aceh	Latitude $\geq 5^\circ$ N
	North Sumatra	Latitude 1° N – $< 5^\circ$ N,
		Longitude $\leq 100^\circ$ E
	West Sumatra	Latitude -2° – $< 1^\circ$ N,
		Longitude $\leq 105^\circ$ E
	West Java	Latitude -7° – $< -2^\circ$ N,
		Longitude $\leq 109^\circ$ E
	East Java	Latitude -8.5° – $< -7^\circ$ N,
		Longitude $\leq 115^\circ$ E
	Bali and NTT	Latitude -9° – $< -8.5^\circ$ N,
		Longitude $\leq 120^\circ$ E
	Sulawesi	Longitude $\leq 122^\circ$ E
	Maluku	Longitude 122° E – 130° E
	Papua	Longitude $> 130^\circ$ E

D. Seismic State Definition

To apply the Markov Chain model, continuous earthquake magnitudes are converted into discrete seismic states. This discretization step is necessary because Markov Chains operate on finite state spaces. Based on commonly used seismic magnitude classifications, seismic states are defined as Table II.

Each time interval is assigned to a seismic state based on the dominant or maximum magnitude of the earthquake observed during that period. These states represent observable seismic activity levels and form the basis of the Markov Chain model.

TABLE II
EARTHQUAKE MAGNITUDE STATE DEFINITION

State Label	Range	Description
M4.0–4.5	< 4.5	No Quake
M4.5–5.0	4.5–5.0	Small
M5.0–5.5	5.0–5.5	Medium
M5.5–6.0	5.5–6.0	Large
M6.0+	≥ 6.0	Very Large

E. Markov Chain Model Construction

The Markov Chain model represents transitions between seismic states over time. Transition probabilities are computed using:

$$P_{ij} = \frac{N_{ij}}{\sum_j N_{ij}} \quad (1)$$

where N_{ij} represents the number of transitions from state i to state j . Future seismic activity probabilities are estimated using:

$$P(X_{n+1}) = P(X_n) \cdot T \quad (2)$$

where $P(X_n)$ is the probability vector of the current state, and T is the transition matrix. For multi-step prediction, the transition matrix is repeatedly applied as:

$$P(X_{n+k}) = P(X_n) \cdot T^k \quad (3)$$

The likelihood of future seismic activity is produced by short term probabilistic projections. The model is then assessed using the Top-1 accuracy, the Top-3 accuracy, and compared against a random baseline. To ensure the prediction pipeline operates correctly, the structured procedure illustrated in figure 1 was followed.

IV. DATA ANALYSIS AND RESULTS

A. Data Characteristics and State Construction

The dataset includes events that happen over time, with a usual time gap of about 0.19 between earthquakes in different areas. This frequency means using the Markov Chain Model to track how one event changes into the next. To make the representation better, each event is shown on its own based on its features like how deep it is, how strong it is, and where it happens. Because of this, these combined traits create 127 possible nations. The table III shows how the model describes each state linked to each attribute and how they are spread out.

B. Transition Matrix Results

The transition matrix represents the probability of moving from one earthquake to another, where each row is normalized and has a sum of one. Figure 2 illustrates the transition probability matrix of the ten most frequent earthquake states, showing that transitions are more likely to occur between states with similar seismic characteristics. Rows represent current states, while columns represent the next states. The intensity indicates the magnitude of the transition probability.

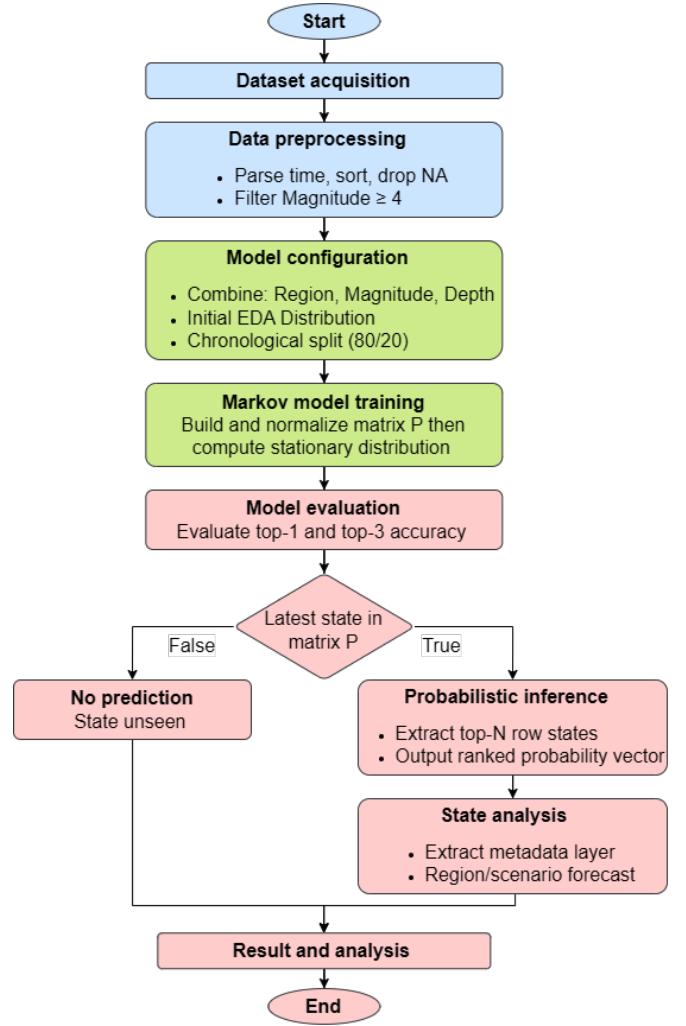


Fig. 1. System Architecture Flowchart.

The results show that the transition matrix is highly sparse, with a sparsity of 79.9% and with many transition probabilities equal to zero. This means that for many state pairs, no transition was observed in the training data. Instead, most of the probability mass is concentrated on a small number of transitions that occur frequently. This behavior is reasonable from a physical perspective. Earthquakes tend to cluster in the same region, and consecutive events often have similar magnitudes and depths. Therefore, transitions between similar states are much more common than transitions between different states. Table IV records the occurrence data of these top ten states.

C. Stationary Distribution Analysis

The stationary distribution represents the probability of the system being in each state after a large number of transitions, regardless of the initial state. Figure 3 reflects the long-term dominance of low-magnitude shallow seismicity in eastern Indonesia and Table V shows that states with low-to-moderate magnitudes, shallow, depths and tectonically active regions

TABLE III
EARTHQUAKE STATE DEFINITION AND DISTRIBUTION

Attribute	State Label	Range	Dist.
Magnitude (M_I)	M4.0–4.5	< 4.5	14364
	M4.5–5.0	4.5–5.0	10892
	M5.0–5.5	5.0–5.5	3800
	M5.5–6.0	5.5–6.0	870
	M6.0+	≥ 6.0	406
Depth (km)	Shallow	< 70 km	1340
	Intermediate	70–300 km	8432
	Deep	> 300 km	20560
Region (Lat./Lon.)	Aceh	Lat. $\geq 5^\circ$ N	1136
	North Sumatra	$1^\circ\text{--}5^\circ$ N, $\leq 100^\circ$ E	2077
	West Sumatra	$-2^\circ\text{--}1^\circ$ N, $\leq 105^\circ$ E	1246
	West Java	$-7^\circ\text{--}-2^\circ$ N, $\leq 109^\circ$ E	12784
	East Java	$-8.5^\circ\text{--}-7^\circ$ N, $\leq 115^\circ$ E	1312
	Bali & NTT	$-9^\circ\text{--}-8.5^\circ$ N, $\leq 120^\circ$ E	4847
	Sulawesi	Lon. $\leq 122^\circ$ E	3535
	Maluku	Lon. $122^\circ\text{--}130^\circ$ E	2255
	Papua	Lon. $> 130^\circ$ E	1137

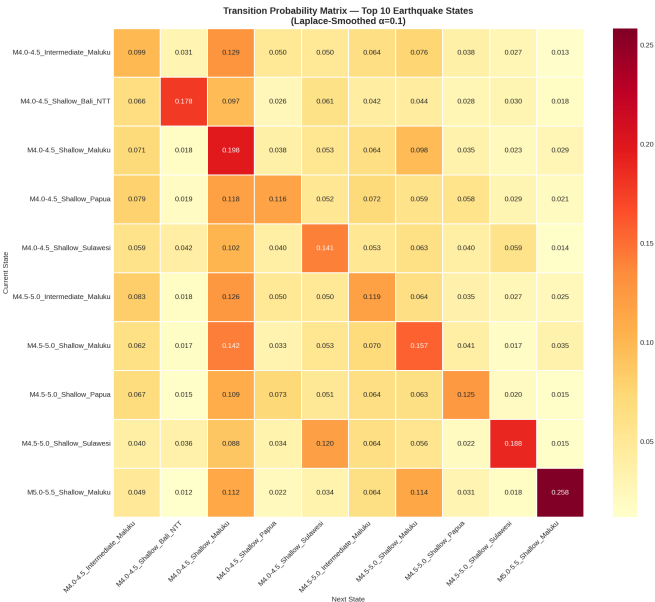


Fig. 2. Transition probability heatmap for the ten most frequent seismic states.

have the highest stationary probabilities. This indicates that, over time, the model spends most of its probability mass on common earthquake types.

This result does not imply that the model is biased. Instead, it reflects the real distribution of earthquake occurrences in Indonesia, where smaller and shallow earthquakes occur much more frequently than large ones. However, this also means that rare but strong earthquakes contribute less to long-term predictions.

TABLE IV
TRANSITION MATRIX FOR TOP TEN MOST FREQUENT STATES

Rank	State Description			Occurrences
	Magnitude	Depth	Region	
1	M4.0-4.5	Shallow	Maluku	2962
2	M4.5-5.0	Intermediate	Maluku	1863
3	M4.0-4.5	Intermediate	Maluku	1628
4	M4.5-5.0	Shallow	Maluku	1498
5	M4.0-4.5	Shallow	Sulawesi	1409
6	M4.5-5.0	Shallow	Papua	1079
7	M4.5-5.0	Shallow	Papua	982
8	M4.5-5.0	Shallow	Sulawesi	737
9	M4.0-4.5	Shallow	Bali and NTT	697
10	M5.0-5.5	Shallow	Maluku	665

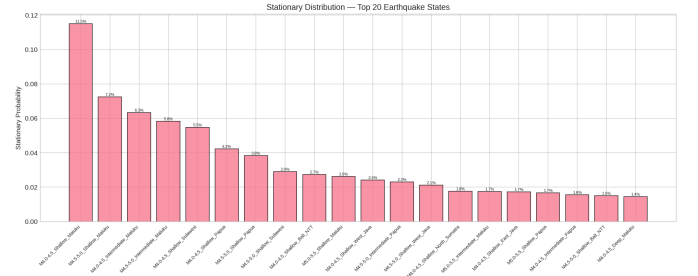


Fig. 3. Stationary probabilities of the top ten seismic states.

D. Prediction Performance Evaluation

To evaluate the prediction performance, the model's results were compared with a random baseline Table VI. Since the system contains 127 states, randomly guessing the next state has a very low probability of success.

The Markov model shows a significant improvement over random guessing. In table VI shows that the prediction of the top 1 is approximately 26 times higher than random, while the prediction accuracy of the top 3 is approximately 17 times higher. These results indicate that the model successfully learns meaningful patterns from historical earthquake sequences.

TABLE V
STATIONARY PROBABILITY OF TOP TEN MOST FREQUENT STATES

Rank	State Description			Probability
	Magnitude	Depth	Region	
1	M4.0-4.5	Shallow	Maluku	12.207%
2	M4.5-5.0	Intermediate	Maluku	7.678%
3	M4.0-4.5	Intermediate	Maluku	6.710%
4	M4.5-5.0	Shallow	Maluku	6.174%
5	M4.0-4.5	Shallow	Sulawesi	5.795%
6	M4.5-5.0	Shallow	Papua	4.447%
7	M4.5-5.0	Shallow	Papua	4.047%
8	M4.5-5.0	Shallow	Sulawesi	3.038%
9	M4.0-4.5	Shallow	Bali and NTT	2.873%
10	M5.0-5.5	Shallow	Maluku	2.740%

TABLE VI
MODEL EVALUATION RESULTS

Classification	Accuracy	Baseline	Improvement factor
Top 1	0.2100	0.0079	26.67x
Top 3	0.3953	0.0236	16.74x

Although the model cannot predict earthquakes with high precision, it significantly narrows the most likely future states.

E. Prediction Results

From Table VII, the total probability covered is 63.67%. The model predicts that the most likely earthquake scenario would occur in Maluku at shallow depth with 4.0–4.5 magnitude.

TABLE VII
TOP TEN PREDICTED NEXT EARTHQUAKE STATES

Rank	Probability	State Description		
		Magnitude	Depth	Region
1	19.85%	M4.0-4.5	Shallow	Maluku
2	9.79%	M4.5-5.0	Shallow	Maluku
3	7.16%	M4.0-4.5	Intermediate	Maluku
4	6.45%	M4.5-5.0	Intermediate	Maluku
5	5.37%	M4.0-4.5	Shallow	Sulawesi
6	3.85%	M4.0-4.5	Shallow	Papua
7	3.48%	M4.5-5.0	Shallow	Papua
8	2.90%	M5.0-5.5	Shallow	Maluku
9	2.53%	M4.5-5.0	Intermediate	Papua
10	2.30%	M4.5-5.0	Shallow	Sulawesi

The model gives greater probabilities of earthquake conditions of comparable size, intensity, and geographical features earlier occurrences, illustrating aftershock patterns and local resilience. However, because of the first-order Markov assumption, the model is unable to accurately detect abrupt significant seismic changes or extended-term connections.

To illustrate the behavior of the proposed model, several ranked prediction scenarios are examined in Tables VIII to XII.

TABLE VIII
SAMPLE PREDICTION SCENARIO I (CURRENT STATE:
M4.0-4.5_SHALLOW_MALUKU)

Rank	Next State Description			Probability
	Magnitude	Depth	Region	
1	M4.0-4.5	Shallow	Maluku	19.85%
2	M4.5-5.0	Shallow	Maluku	9.79%
3	M4.0-4.5	Intermediate	Maluku	7.16%

These results show strong regional persistence, as the predicted earthquake states consistently remain within the same geographic region as the current event. The model also shows

TABLE IX
SAMPLE PREDICTION SCENARIO II (CURRENT STATE:
M4.0-4.5_SHALLOW_MALUKU)

Rank	Next State Description			Probability
	Magnitude	Depth	Region	
1	M4.5-5.0	Shallow	Maluku	15.78%
2	M4.0-4.5	Shallow	Maluku	14.33%
3	M4.5-5.0	Intermediate	Maluku	7.03%

TABLE X
SAMPLE PREDICTION SCENARIO III (CURRENT STATE:
M4.0-4.5_INTERMEDIATE_MALUKU)

Rank	Next State Description			Probability
	Magnitude	Depth	Region	
1	M4.0-4.5	Shallow	Maluku	12.96%
2	M4.0-4.5	Intermediate	Maluku	9.95%
3	M4.5-5.0	Shallow	Maluku	7.62%

magnitude and depth continuity, favoring gradual transitions over abrupt seismic changes, which reflects common after-shock behavior. Although probability values are relatively low due to larger state space, the prediction rankings remain meaningful. In general, the model prioritizes physically plausible seismic transitions, indicating interpretable and statistically informed probabilistic forecasting behavior.

F. Model Limitations and Discussion

The proposed model has several limitations. First, it only captures short-term dependencies and cannot represent the

TABLE XI
SAMPLE PREDICTION SCENARIO IV (CURRENT STATE:
M4.5-5.0_INTERMEDIATE_MALUKU)

Rank	Next State Description			Probability
	Magnitude	Depth	Region	
1	M4.0-4.5	Shallow	Maluku	12.68%
2	M4.0-4.5	Intermediate	Maluku	12.02%
3	M4.0-4.5	Intermediate	Maluku	8.34%

TABLE XII
SAMPLE PREDICTION SCENARIO V (CURRENT STATE:
M4.0-4.5_SHALLOW_SULAWESI)

Rank	Next State Description			Probability
	Magnitude	Depth	Region	
1	M4.0-4.5	Shallow	Sulawesi	14.22%
2	M4.0-4.5	Shallow	Maluku	10.31%
3	M4.5-5.0	Shallow	Maluku	6.33%

accumulation of long term tectonic stress. Second, sparse transitions reduce the prediction reliability of rare earthquake states, particularly high magnitude events. Beyond its analytical contribution, the probabilistic output of the proposed model is well-suited for integration into early warning system architectures. This framework can be applied in resource constrained monitoring environments in seismically active regions.

V. CONCLUSION AND RECOMMENDATIONS

This study used a first-order Markov Chain model to examine earthquake state transitions in Indonesia, by analyzing factors such as magnitude, depth, and regional information. The results show that the transition matrix successfully captures short term seismic dependencies in similar states. Stationary distribution analysis indicates that low and moderate magnitude and shallow categories dominate long term seismic behavior. Performance evaluation demonstrates that the proposed model significantly outperforms random prediction baselines, achieving a Top-1 accuracy of 21.00% and a Top-3 accuracy of 39.53%, representing a respective performance increase by a factor of 26.67 and 16.74 over the baseline metrics.

Future research can develop this framework by transitioning to higher order or hidden Markov models to capture long term temporal dependencies and latent geophysical conditions. In improving prediction reliability for high-magnitude events, advanced sparsity handling techniques such as Laplace smoothing, back-off strategies, or adaptive state grouping should be implemented. Furthermore, developing hybrid architectures that combine the transparent Markov structure with deep learning networks would allow the framework to exploit probabilistic clarity and deep feature extraction capabilities. Finally, the framework's operational utility can be extended by deploying the inference pipeline directly onto distributed sensor networks for real cases with using larger seismic datasets.

DATA AVAILABILITY

The dataset used in this study can be accessed via Kaggle. "Earthquakes in Indonesia" at <https://www.kaggle.com/datasets/kekavigi/earthquakes-in-indonesia/data> or at the following DOI: <https://doi.org/10.34740/kaggle/dsv/13265963>.

AUTHOR'S CONTRIBUTIONSHIP

Dian Rakhmawati Lestari: Literature Review, Software, Data Visualization, and Writing. **Emmanuel Keith Hadipradja:** Abstraction, Introduction, Literature Review. **Latasha Ivy Khoe:** Data Analysis, Results, and Writing. **Nadya Salsabila:** Research Methodology, Writing. **Selvi Lukman** and **Yasi Dani:** Validation and Review.

ACKNOWLEDGMENT

The authors used Gemini and ChatGPT for code optimization and language refinement. All AI-assisted outputs were manually verified, and the authors remain fully responsible for this study.

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