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Article

Utilizing long short-term memory (LSTM) networks for predicting seismic-induced building damage: a Bawean Region case study

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***Abstract*—This study examines the feasibility of employing Long short-term memory (LSTM) networks to estimate earthquake-induced building damage using a focused dataset derived from the continuous 8-day mainshock–aftershock sequence that occurred in March 2024. A total of 483 events were analyzed, utilizing three readily available source parameters: magnitude, depth, and epicentral distance to predict the corresponding EMS-98 damage grade. The motivation for using an LSTM architecture stems from its capacity to model temporal dependencies in sequential seismic activity, despite the dataset's limited size. The best-performing single-split model (B4) achieved a test R^2 of 0.5738 and an RMSE of 0.2997 on the held-out set. However, to obtain a more robust assessment of the model's generalizability, a 5-fold TimeSeriesSplit cross-validation was conducted. The cross-validation procedure yielded a mean R^2 of 0.49 with a standard deviation of 0.27, and a mean RMSE of 0.33 with a standard deviation of 0.16. These results demonstrate that the LSTM model provides a credible baseline for exploratory damage estimation. However, a substantial portion of the variance remains unexplained due to the absence of geotechnical, soil-amplification, and structural-fragility information. The findings highlight the potential of sequence-based modeling for rapid damage estimation and underscore the need for integrating site-specific and structural variables in future work to enhance predictive accuracy.**

***Keywords*— disaster mitigation; lstm; prediction of building damage; seismic data; tectonic earthquakes.**

1. Introduction

Indonesia's geographical position at the confluence of the Eurasian, Indo-Australian, Pacific, and Philippine microplates render it highly susceptible to significant seismic hazards (Prasetyo et al., 2024; Susilo et al., 2026). This vulnerability is underscored by a marked escalation in seismic activity; annual event counts, which previously ranged from 4,000-5,000, have surpassed 10,000 since 2019 (Ekaptiningrum, 2024), (Pusat Studi Gempa Nasional, 2022). Data from the Malang Geophysics Station further corroborates this trend, documenting 8,539 distinct earthquakes in East and Central Java during 2024 (Geophysics, 2024). Within this context, the Bawean region presents a case of heightened vulnerability owing to the presence of two major tectonic fault systems (Manur, 2018),

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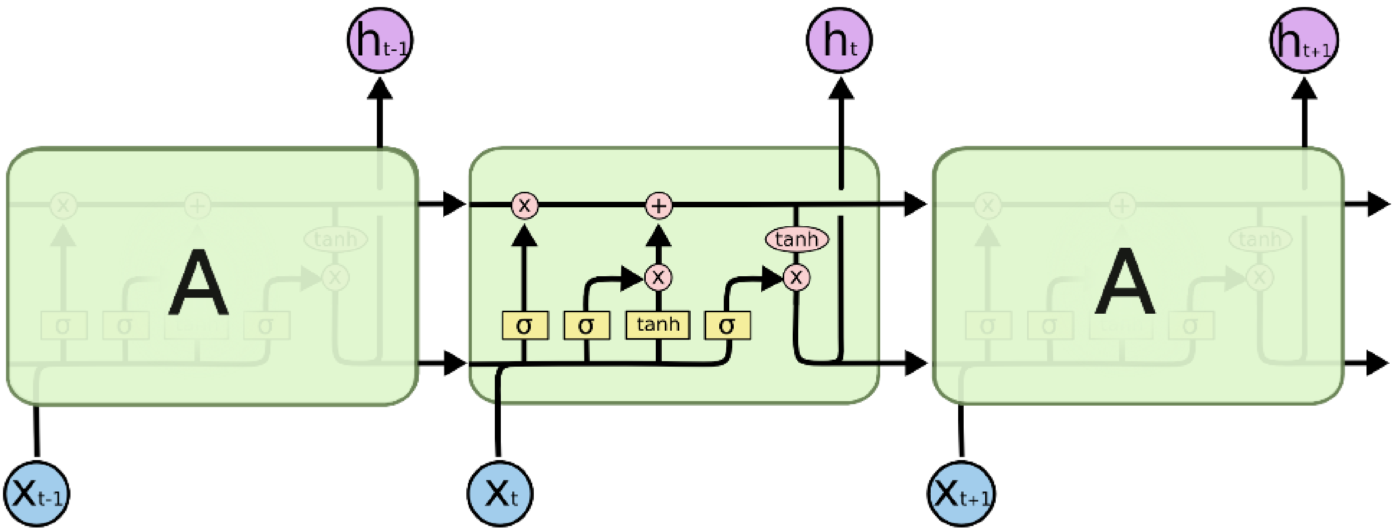


Fig. 1. Long short-term memory (LSTM) architecture.

(Almais et al., 2024). Consequently, the development of more effective post-earthquake damage assessment methodologies has become a critical imperative (Almais et al., 2025).

While prior research, such as Almais et al. (2023), has employed methods like Principal Component Analysis (PCA) and clustering for evaluating disaster impact (Pak & Paal, 2025), this study pioneers a forecasting-based methodology (Whittaker et al., 1999). This methodological shift is motivated by the limitations of conventional approaches and the potential demonstrated by advanced time-series analysis (Hao et al., 2025). The long short-term memory (LSTM) model was selected for this research due to its recognized efficacy in analyzing historical time-series data and discerning complex temporal seismic patterns (Rifaldi & Ahdika, 2024; Senkaya et al., 2024; Takagi & Wada, 2019). A gap remains in quantifying the specific predictive power of readily available seismological source data in isolation. This knowledge is crucial for rapid, first-response assessments when detailed site data is unavailable. Specifically forecasting post-earthquake building damage, this study aims to provide a quantitative tool to bolster risk mitigation strategies (Juanara & Lam, 2025), inform sustainable development planning (Bai & Tahmasebi, 2022), and enhance preparedness protocols, particularly in high-risk areas like Bawean (Manur, 2018). The resulting model is envisioned as a critical analytical tool for agencies such as BMKG, facilitating more effective, data-driven emergency response and strategic decision-making.

Therefore, the primary objective of this study is twofold: first, to establish the baseline predictive performance of a long short-term memory (LSTM) network using only three fundamental seismological parameters (magnitude, depth, distance). Second, this research aims to critically evaluate and quantify the explanatory gap resulting from excluding non-seismic factors, namely geotechnical and structural properties. By focusing on the 483 event mainshock-aftershock sequence from the March 2024 Bawean earthquake, this study serves as a foundational investigation into the potential and inherent limitations of this data-driven approach.

2. Research Method

2.1. Study area, dataset, and features

The Bawean region ($5°43' - 5°52' S, 112°33' - 112°45' E$) was selected as the study area due to its high seismic vulnerability. The dataset utilized in this study comprises 483 distinct aftershock events recorded by the Meteorological, Climatological, and Geophysical Agency (BMKG) following the main shock of the March 2024 Bawean earthquake. These events were captured over an eight-day period, yielding a unique sequential dataset suitable for time-series analysis.

For each event, three fundamental seismological parameters, which are typically available in real-time, were selected as input features: (1) Magnitude (M_w), (2) Depth (km), and (3) Epicentral Distance (km). The output variable for prediction was the corresponding building damage level. The building damage levels were categorized based on the EMS-98 scale and normalized between 0 and 1 for model training.

2.2. Data preprocessing

The dataset comprises 483 earthquake events recorded throughout March 2024, with the following parameter distributions:

a. Magnitude: Ranging from 2.5 to 6.5 M_w (Mean: 3.3, SD: 0.5)
b. Depth: Varying from 10 to 35 km (Mean: 10.3 km, SD: 1.7)
c. Epicentral Distance: 101-171 km (Mean: 135.1, SD: 9.4) from Bawean urban center. The building damage levels were categorized based on the EMS-98 scale (J. Li et al., 2019), with values normalized between 0 and 1 for model training. The data pre-processing stage included cleaning and standardization. Data normalization was performed using the MinMaxScaler from the Python library to standardize the scale of each feature. The MinMaxScaler normalization was chosen for its ability to maintain the

original form of the data distribution and is effective for algorithms that do not assume Gaussian distributions such as LSTMs. In contrast to Z-Score Standardization, MinMaxScaler scales data to the [0, 1] range, thereby accelerating convergence during training (Whittaker et al., 1999). The formula used is as follows:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

2.3. Method

This research methodology comprises two main stages: data preparation and the implementation of the proposed method. The initial stage used 2024 earthquake data from the Badan Meteorologi, Klimatologi, Geofisika (BMKG), comprising 483 data points for the Bawean region in East Java. The primary parameters used as model inputs were earthquake depth (km), magnitude, and epicentral distance to the nearest city (km).

The proposed method is the implementation of long short-term memory (LSTM), as shown in Fig. 1, a forecasting technique highly suitable for time-series data such as seismic data (Jalayer & Ebrahimian, 2019). LSTM operates through a series of 'gates' that regulate the flow of information: the forget gate, input gate, and output gate (Senkaya et al., 2024). This structure enables the LSTM to store and access information over long periods, thereby overcoming the vanishing-gradient problem observed in traditional RNNs.

The developed LSTM model architecture consists of three primary layers: an input layer containing three neurons (corresponding to the number of parameters), a hidden layer with 128 neurons employing the ReLU activation function and a dropout rate of 0.2 to prevent overfitting, and an output layer with a single neuron utilizing a linear activation function to predict the damage level (Hartono et al., 2025; Hochreiter & Schmidhuber, 1997). The model was compiled using the Adam optimizer with a learning rate of 0.001 and the Mean Squared Error (MSE) as the loss function (Takagi & Wada, 2019).

To evaluate the predictive model's performance, two primary metrics were used: Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2). Root Mean Square Error (RMSE) is a metric that measures the average magnitude of errors between predicted and actual values. RMSE gives a higher weight to larger errors and is expressed in the same units as the target variable (Azis et al., 2020). A lower RMSE value indicates better model performance. The formula for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

Where n is the sum of data, y_i is the actual value, and $\hat{y}_i$ is the predictive value. Coefficient of Determination (R^2) is a metric that quantifies the proportion of variance in the dependent variable that can be predicted from the independent variable(s). The R^2 value ranges from 0 to 1, where a value closer to 1 indicates that the model explains a large portion of the data variability. The formula for R^2 is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

Where $\bar{y}$ is the average value of the actual data. The data was partitioned using an 85% training-validation split, with the model trained over 500 epochs. Model performance was evaluated using Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2) metrics to assess predictive accuracy.

2.4. Model Optimization and Validation

To determine the optimal model architecture and data partitioning strategy, a rigorous optimization process was conducted. The dataset was divided using three distinct training-testing splits, defined as:

a. Group A: 60% training data, 40% testing data
b. Group B: 70% training data, 30% testing data
c. Group C: 80% training data, 20% testing data

Hyperparameter tuning (including variations in LSTM layers, dense layers, epochs, and batch size) was performed across these three groups. The model's performance was evaluated based on its generalizability to the unseen test dataset, prioritizing the Coefficient of Determination (R^2) and Root Mean Square Error (RMSE). As detailed in the Results section, the Model B4 configuration, derived from the Group B split (70/30), was identified as the architecture with the best overall performance.

2.5. Cross-Validation Using TimeSeriesSplit

To evaluate the generalization stability across temporal segments of the LSTM model and ensure that its performance was not dependent on a single random split, a 5-fold cross-validation was conducted using the TimeSeriesSplit method. Unlike conventional random K-fold cross-validation, TimeSeriesSplit preserves the chronological order of seismic events by ensuring that the training folds always consist of earlier events and testing folds consist of later events. This structure prevents temporal leakage and more accurately reflects real-world forecasting conditions, in which future seismic events cannot be predicted from future information.

For each fold, a new LSTM model was trained from scratch using the same architecture and hyperparameters as the optimal Model B4. Model performance was evaluated using both the Coefficient of Determination (R^2) and Root Mean Square Error (RMSE). The final performance metrics are reported as the average and standard deviation across all folds to represent the model's stability.

3. Result

This section presents the empirical outcomes of the optimized LSTM models. The performance was evaluated based on the Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) on the unseen test dataset.

3.1. Model Performance

Following hyperparameter tuning across different data splits (Groups A, B, and C), the Model B4 configuration was identified as the optimal predictor. This model, corresponding to a 70% training and 30% testing data split (Group B), yielded the most

Table 1. Performance results of model groups A, B, and C

Model	Split Dataset	Train RMSE	Test RMSE	Train R^2	Test R^2
A1	60:40	0.2338	0.3592	0.8288	0.3541
A2	60:40	0.2701	0.3626	0.7715	0.3419
A3	60:40	0.1979	0.3512	0.8773	0.3823
A4	60:40	0.1970	0.3635	0.8784	0.3384
B1	70:30	0.2570	0.3106	0.7775	0.5423
B2	70:30	0.2534	0.3023	0.7838	0.5663
B3	70:30	0.2533	0.3021	0.7839	0.5668
B4	**70:30**	**0.2497**	**0.2997**	**0.7900**	**0.5738**
C1	80:20	0.2461	0.3329	0.7837	0.5022
C2	80:20	0.2460	0.3249	0.7838	0.5260
C3	80:20	0.2433	0.3208	0.7885	0.5380
C4	80:20	0.2429	0.3256	0.7892	0.5240

Table 2. 5-fold cross validation

Fold	RMSE	R^2
1	0.5801	0.4725
2	0.0920	0.9563
3	0.3033	0.2037
4	0.3823	0.2553
5	0.3105	0.5565
Mean	**0.3336**	**0.4889**
Std	**0.1568**	**0.2680**

robust and generalizable results.

The performance metrics for the optimal model are detailed in Table 1. Model B4 achieved a Test R^2 of 0.5738 and a Test RMSE of 0.2997. The training R^2 (0.7900) and training RMSE (0.2497) indicate a well-fitted model, though a degree of variance remains unexplained in the test data, as expected.

3.2. Cross-Validation using TimeSeriesSplit

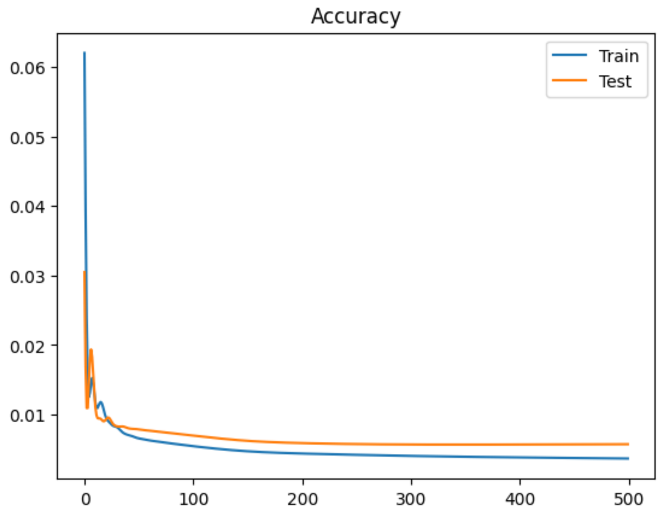
To further evaluate Table 2, the stability and generalizability of the LSTM model across different temporal segments were assessed using a 5-fold TimeSeriesSplit cross-validation. The evaluation metrics for each fold revealed varying levels of predictive performance, reflecting the small dataset size and the limited number of input features (magnitude, depth, distance).

The cross-validation resulted in an average R^2 of 0.4889 (Std: 0.2680) and an average RMSE of 0.3336 (Std: 0.1568). This variation indicates that, although the model can learn a meaningful predictive pattern from sequential data, its accuracy is influenced by the characteristics of each temporal fold.

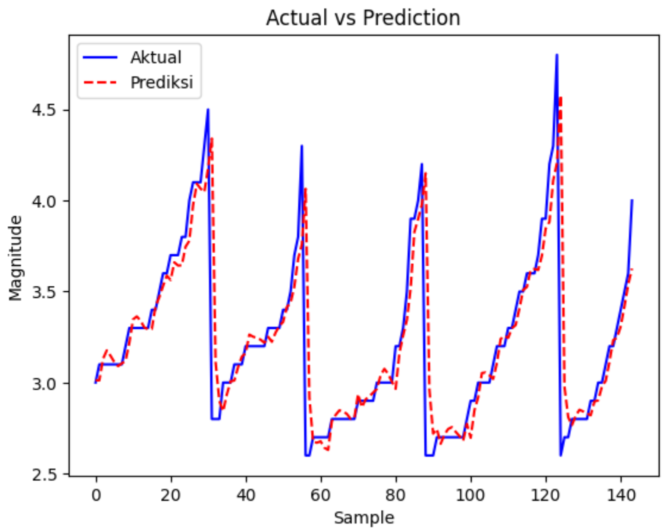
These results confirm that the model performs reasonably well as a baseline estimator but remains sensitive to the limited information available from source parameters alone.

3.3. Visual Analysis of Model Predictions

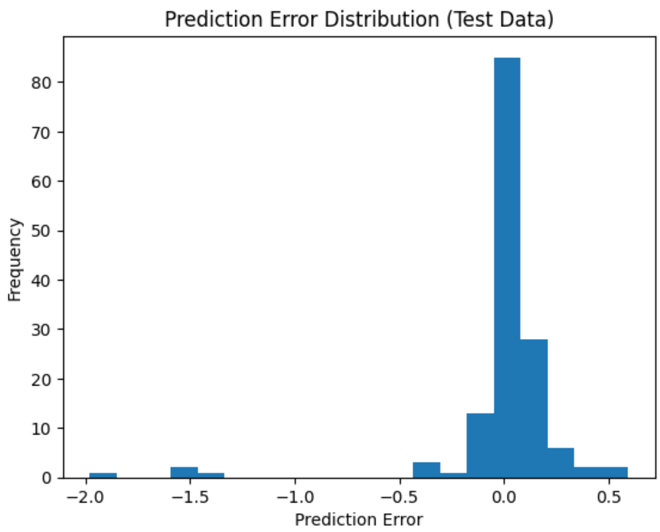
Visual analysis of the model's predictions provides further insight into its performance. Fig. 2(b) presents a time-series



(a) Loss (MSE) convergence curve over 500 epochs



(b) Time-series sample comparison



(c) Error distribution histogram

Fig. 2. Model B4 performance visualization.

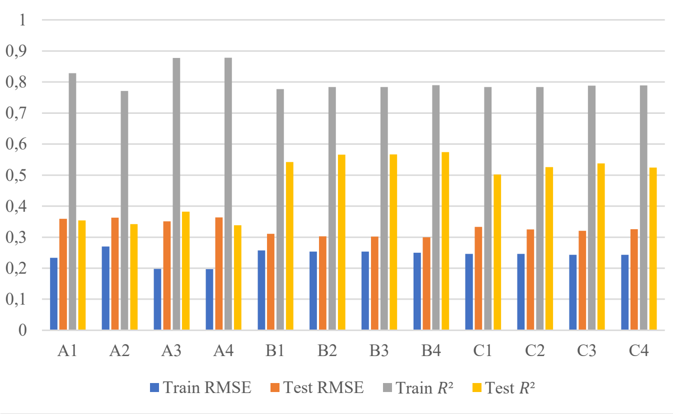


Fig. 3. Graph of model A, B, and C results.

comparison of actual damage values with those predicted by Model B4 on the test dataset. The plot demonstrates that the model successfully captures the overall trend and fluctuations of the damage sequence.

Fig. 2(c) presents the histogram of errors for the test-set predictions. This plot, which replaces the previous uninterpretable chart, confirms that the prediction errors are centered near zero and approximate a normal distribution. This indicates that the model exhibits low average systematic bias, thereby validating a key assumption of the regression analysis.

Samples in Fig. 2(b) are ordered chronologically according to the 8-day mainshock–aftershock sequence. The connecting line represents the temporal progression of seismic events. The x-axis represents the chronological order of the aftershock events rather than a magnitude-based or randomized ordering. Therefore, the connecting line accurately illustrates the temporal progression inherent to the dataset.

Fig. 3 illustrates the performance stability across all models in Groups A, B, and C, which serves as a positive indicator of the model's generalization capacity when trained with sufficient data. This suggests that the chosen architecture has reached an optimal point for the current dataset, beyond which further increases in model complexity may not yield significant improvements.

4. Discussion

This section interprets the findings presented in the Results, addresses the methodological choices, and explicitly discusses the study's limitations.

4.1. Interpretation of Predictive Capability

Seismic aftershock sequences inherently exhibit temporal dependence due to stress redistribution and cascading fault interactions following the mainshock. These processes generate correlated patterns in magnitude, depth, and spatial propagation over time. LSTM networks are well-suited for such sequential data because their memory cells and gating mechanisms enable them to retain information across previous time steps. Thus, even with a relatively small dataset (483 events), the chronological structure of the data makes LSTM a scientifically reasonable candidate architecture for modeling the evolving patterns of seismic-induced damage.

Given that the damage level was normalized between 0 and 1 based on the EMS-98 scale, the Test RMSE of 0.2997 corresponds to an average deviation of approximately 0.30 damage grades. This means that the model's typical prediction error falls within approximately one-third of a damage level on the EMS-98 scale, thereby improving interpretability in real-world damage assessment contexts.

The primary finding of this study is that the optimal LSTM model (B4) achieved an R^2 of 0.5738. This result is central to the paper's contribution: it quantifies that 57.38% of the variance in building damage is explained solely by seismic source parameters. This result reinforces the broader requirement that predictive models demonstrate adequate robustness to be considered operationally meaningful. Ensuring model robustness is essential for establishing reliable predictive performance in real-world scenarios. This R^2 value signifies a statistically significant predictive power for baseline estimation. However, it also explicitly quantifies the limitations of an underspecified model. The remaining 42.62% of random variation is substantial and is strongly hypothesized to be driven by the critical variables not included in this study's scope:

a. Geotechnical Factors: Local site conditions, soil amplification, and liquefaction potential.
b. Structural Factors: Building typology, age, design codes, and construction material quality.

Therefore, this model is not intended to serve as a comprehensive predictive solution, but rather as a foundational baseline that demonstrates the predictive power and limitations of relying solely on seismological data for rapid damage assessment.

4.2. Methodological Rationale and Data Constraints

The selection of an LSTM network, typically applied to time-series data, was a deliberate methodological choice. The dataset of 483 events represents a continuous 8-day mainshock-to-aftershock sequence. We hypothesized that LSTM architecture is uniquely suited to capture potential temporal dependencies or cumulative damage patterns within this specific sequence, which static regression models might overlook. In contrast to the previous study by Almais (2023), which employed PCA-Clustering on a static dataset (Almais et al., 2023). The LSTM forecasting approach provides an alternative perspective by analyzing temporal patterns.

We explicitly acknowledge the limitations identified by the reviewer regarding the dataset. A dataset of 483 data points is modest for deep learning applications. Furthermore, using data exclusively from the March 2024 Bawean aftershock sequence introduces significant temporal and geographical bias. The model is therefore highly specialized for this type of seismic event. We have added a statement in the conclusion clarifying that the model's generalizability to different tectonic settings or mainshock events is not guaranteed and requires validation on more diverse datasets.

4.3. Analysis of Residuals and Prediction Bias

The error distribution histogram (Fig. 2(c)) addresses the previous concerns regarding interpretability. It clearly shows that the prediction errors are essentially symmetrically distributed around zero, indicating that the model is not systematically over- or under-predicting on average.

However, a closer analysis of the time-series plot in Fig. 2(b) addresses the concern of systematic bias. While Model B4 tracks the data significantly better, it still tends to underpredict the highest damage peaks. This systematic under-prediction of extreme events is a common challenge in regression modeling. This suggests that while the model captures the mean trend effectively ($R^2 = 0.5738$), it struggles with the nonlinearity of the most severe damage events. This limitation is explicitly articulated to clarify its implications for interpreting the model's predictive behavior.

For future research, several development paths can be explored:

a. Integration of Additional Features: Incorporating geotechnical data and building quality data into the model to enhance predictive accuracy.
b. More Rigorous Validation: Applying cross-validation techniques, such as k-fold cross-validation, to ensure better model reliability and generalization.
c. Hybrid Models: Developing hybrid models that integrate LSTM with other methods, such as Convolutional Neural Networks (CNN) for spatial feature extraction or clustering for seismic pattern segmentation before forecasting.

The model consistently under-predicts extreme damage levels, which is physically reasonable given the absence of critical explanatory variables. Local site effects, including soil amplification, basin resonance, soft-soil pockets, and liquefaction susceptibility, strongly influence peak building damage. Prior studies have shown that these geotechnical and structural factors can account for approximately 30–50% of the total variation in earthquake-induced damage. Since the present model uses only source parameters magnitude, depth, and epicentral distance, it lacks the information necessary to capture these nonlinear local amplification effects. Consequently, the LSTM tends to learn the average expected damage profile while underestimating outlier peaks. These findings are consistent with prior studies demonstrating the significant influence of soil amplification and structural fragility on the upper tail of damage distributions (Almais et al., 2023; J. Li et al., 2019; Senkaya et al., 2024).

4.4. Influence of Missing Geotechnical and Structural Variables

Several studies have quantified the significant role of local soil conditions and structural characteristics in the variability of earthquake damage. Site amplification, liquefaction, and building fragility curves have been shown to contribute between 30–50% of the observed variation in structural damage during earthquakes. The 42.62% unexplained variance identified in this study aligns well with these findings, indicating that the absence of geotechnical and structural parameters in the current model is a major contributor to the remaining prediction error. This reinforces the conclusion that, although the proposed LSTM model provides a meaningful baseline using only source parameters, a more comprehensive dataset is necessary to achieve greater predictive reliability. This interpretation aligns with previous findings, underscoring the significant contribution of soil characteristics and structural typology to damage variability (T. Li et al., 2019; Pak & Paal, 2025; Senkaya et al., 2024).

5. Conclusion

This study investigated the feasibility and limitations of using LSTM networks for predicting seismic-induced building damage from seismological source parameters alone. The research identified an optimal configuration, Model B4, which achieved a Coefficient of Determination (R^2) of 0.5738 and a Test RMSE of 0.2997 on a sequential dataset of 483 aftershock events. The primary contribution of this research is the establishment of a quantitative performance baseline. The R^2 value demonstrates that while earthquake source data alone has significant predictive power (explaining 57.38% of the variance in damage), a substantial portion (42.62%) remains unexplained. This finding empirically confirms that the model is underspecified and underscores the necessity of integrating non-seismic parameters, such as local soil conditions and building structural data, to develop a reliable predictive tool. This study also explicitly acknowledges its limitations, including the modest dataset size and the potential for temporal and geographical biases associated with using a single aftershock sequence. Future research should prioritize integrating additional features, particularly geotechnical and structural data, to bridge the explanatory gap identified in this work. Furthermore, applying more rigorous validation techniques, such as k-fold cross-validation, and exploring hybrid models (e.g., CNN-LSTM) are recommended to enhance model robustness and generalization in real-world disaster mitigation applications.

The cross-validation evaluation using a 5-fold TimeSeriesSplit produced an average RMSE of 0.33 (Std = 0.16) and a mean R^2 of 0.49 (Std = 0.27), confirming that the LSTM model offers a meaningful baseline for sequence-based damage estimation using only source parameters. While the optimal single-split performance reached R^2 = 0.5738 on the held-out test set, the cross-validation mean provides a more reliable estimate of the model's expected predictive behavior under realistic operational conditions. Approximately 42.6% of the variance remains unexplained, emphasizing the need to incorporate geotechnical factors, soil amplification characteristics, and structural fragility indicators in future work to improve model accuracy and ensure broader generalization.

Data Availability

The dataset supporting this study has been deposited in Zenodo and is publicly available at: https://doi.org/10.5281/zenodo.17804934

Declaration of Competing Interest

The authors affirm that they have no known financial competing interests or personal connections that could be perceived to have affected the research presented in this article.

Authors' Contributions

Ahmad Zarkoni: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Visualization. **Agung Teguh**

Wibo Almais: Conceptualization, Methodology, Validation, Resources, Writing – Review & Editing, Supervision, Project administration, Funding acquisition. **Cahyo Crysdian**: Validation, Writing – Review & Editing, Supervision. Mokhamad **Amin Hariyadi**: Validation, Writing – Review & Editing, Visualization. **Usman Pagalay**: Validation, Writing – Review & Editing. **Tomy Ivan Sugiharto**: Data Curation, Validation, Methodology, Writing – Review & Editing.

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