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Comparative Evaluation of CNN, LSTM, and GRU Architectures for Tsunami Prediction Using Seismic Data

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Abstract

Tsunamis are among the most catastrophic natural disasters, often triggered by seismic events such as earthquakes. Accurately predicting tsunami occurrences based on seismic parameters is critical for mitigating their devastating impacts. This study investigates the application of three advanced deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and Gated Recurrent Units (GRUs) for binary classification of tsunami events using seismic data. The dataset comprises earthquake records from 1995 to 2023, including features such as magnitude, depth, latitude, longitude, Modified Mercalli Intensity (MMI), and Community Internet Intensity (CDI). The models were evaluated using stratified 10-fold cross-validation and assessed across precision, recall, F1-score, accuracy, and ROC-AUC metrics. Results indicate that CNN outperformed the other architectures, achieving the highest accuracy (72.5%), precision (0.5987), and ROC-AUC (0.7838). GRU demonstrated moderate performance, balancing computational efficiency and predictive accuracy with an accuracy of 71.7% and ROC-AUC of 0.7709. LSTM, while theoretically adept at modeling temporal dependencies, showed the lowest performance due to challenges in capturing the dataset's characteristics. The findings emphasize the importance of selecting architecture suited to the dataset's features and task requirements. CNN's superior performance highlights its effectiveness in spatial pattern extraction, while GRU offers a computationally efficient alternative. Future work will explore hybrid models and the integration of additional features to enhance prediction robustness. This study contributes to advancing tsunami prediction methodologies, supporting early warning systems for disaster preparedness.

Keywords: *Tsunami Prediction, Deep Learning, Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), Gated Recurrent Units (GRUs)*

1. Introduction

The catastrophic impacts of tsunamis, driven by seismic activities such as earthquakes, pose severe threats to human lives, infrastructure, and economic stability [1]–[3]. Despite advancements in seismology, predicting the occurrence of tsunamis based on seismic parameters remains a critical challenge due to the complexity of their underlying dynamics [4]–[6]. Accurate prediction systems are essential for timely disaster response and mitigation, especially in regions highly susceptible to seismic hazards [7]–[9]. In this study, we propose a robust deep learning framework for tsunami prediction, leveraging historical earthquake data collected globally between 1995 and 2023. Recent advancements in machine learning and deep learning have revolutionized predictive modeling across various domains, including healthcare, finance, and environmental sciences. Among these advancements, deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and Gated Recurrent Units (GRUs) have demonstrated remarkable performance in extracting spatial, temporal, and sequential patterns from complex datasets. CNNs are highly effective in capturing localized patterns in high-dimensional data, while LSTMs and GRUs are

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tailored for modeling long-term dependencies, making them suitable for sequential data such as seismic records [10]–[12]. However, a comprehensive comparative evaluation of these architectures for tsunami prediction using global earthquake data has not been extensively explored in the literature.

Existing approaches to tsunami prediction predominantly rely on statistical models or traditional machine learning techniques, which often fail to capture the intricate relationships between seismic parameters such as magnitude, depth, latitude, and longitude [13]–[15]. Moreover, the lack of rigorous cross-validation frameworks and imbalanced class distributions in previous studies has limited the generalizability and reliability of their predictive models [16]–[18]. These challenges underline the necessity for a more sophisticated methodology that integrates advanced deep learning models validated through robust experimental setups [19]–[21]. This research addresses these gaps by employing CNN, LSTM, and GRU architectures for binary classification of tsunami occurrence. The dataset used in this study comprises seismic parameters, including magnitude, depth, latitude, longitude, Modified Mercalli Intensity (MMI), and Community Internet Intensity (CDI), which are preprocessed through imputation of missing values, normalization using MinMax scaling, and transformation for compatibility with sequential models. The target variable, indicating whether an earthquake triggered a tsunami, is modeled as a binary classification problem to evaluate the predictive capabilities of the proposed models.

A stratified 10-fold cross-validation approach was implemented to ensure balanced representation of the minority class and robust performance evaluation. Each model architecture was designed to exploit specific data characteristics: CNNs for spatial feature extraction, LSTMs for capturing temporal dependencies, and GRUs as computationally efficient alternatives for sequence modeling. The models were trained using the Adam optimizer with a binary cross-entropy loss function, and their performance was assessed using metrics such as accuracy, precision, recall, F1-score, and area under the Receiver Operating Characteristic curve (ROC-AUC). This study contributes to the state-of-the-art by presenting a systematic evaluation of advanced deep learning models for tsunami prediction using a large-scale, real-world dataset. The findings highlight the potential of deep learning to enhance the accuracy and reliability of tsunami prediction systems, providing a foundation for future research into hybrid architectures and real-time predictive solutions. Future work will explore the integration of additional data sources, such as oceanographic and atmospheric variables, to further improve predictive capabilities and support disaster mitigation strategies globally. The remainder of this article is organized as follows: Section 2 describes the dataset and preprocessing pipeline, detailing the features, target variable, and transformations applied to prepare the data for modeling. Section 3 introduces the proposed methodology, including the architectures of CNN, LSTM, and GRU models, their configurations, and the stratified cross-validation approach used for evaluation. Section 4 presents the experimental results, offering a detailed comparative analysis of the models across various performance metrics and folds. Finally, Section 5 concludes the article, summarizing the key contributions and emphasizing the importance of integrating deep learning techniques in disaster prediction systems.

2. Research Methodology

2.1. Dataset and Preprocessing

The dataset utilized in this study encompasses global earthquake records spanning from 1995 to 2023, providing a comprehensive representation of seismic activities and their associated parameters and can be downloaded from [22]. The primary features included in the dataset are magnitude, latitude, longitude, depth, Modified Mercalli Intensity (MMI), and Community Internet Intensity (CDI). The target variable, tsunami occurrence, is modeled as a binary classification problem where $y \in \{0, 1\}$, with $y = 1$ indicating the presence of a tsunami and $y = 0$ signifying its absence. The dataset is characterized by a significant class imbalance, as most earthquakes do not result in tsunamis. This imbalance necessitated specialized preprocessing steps to ensure the dataset's suitability for training robust and generalizable predictive models.

Initially, the dataset was cleaned by addressing missing values and removing incomplete records in critical features such as magnitude (M), latitude (ϕ), longitude (λ), depth (D), and tsunami occurrence (T). For secondary features, including MMI and CDI, missing values were imputed using the median of the respective feature, denoted mathematically as (1).

$$\mathrm{MMI}_{\mathrm{imputed}} = \mathrm{median}(\mathrm{MMI}), \quad \mathrm{CDI}_{\mathrm{imputed}} = \mathrm{median}(\mathrm{CDI}) \qquad (1)$$

This approach preserved the overall statistical distribution while minimizing information loss. To normalize the numerical range of features and improve model convergence, Min-Max Scaling was applied to all input variables. For a feature X_i, the normalized value $X_{\mathrm{scaled},i}$ was computed as (2).

$$X_{\mathrm{scaled},i} = \frac{X_i - \min(X)}{\max(X) - \min(X)} \qquad (2)$$

This transformation maps all feature values to the range $[0,1]$, ensuring uniformity across variables with different scales, such as magnitude, which typically ranges between 2.0 and 9.5, and depth, which spans from near-surface to hundreds of kilometers. The target variable was processed for binary classification. The original tsunami labels were transformed into a binary format, expressed mathematically as (3).

$$y_i = \{1 \text{ if a tsunami was triggered by the earthquake, 0 otherwise.}\} \qquad (3)$$

Given the imbalance in the target classes, additional preprocessing techniques such as Synthetic Minority Oversampling Technique (SMOTE) were explored in some experimental configurations. SMOTE generates synthetic samples for the minority class by interpolating between existing instances, effectively balancing the dataset. To prepare the data for deep learning models, the feature matrix X was reshaped into three-dimensional tensors, ensuring compatibility with sequential models. Specifically, for a dataset with n samples and m features, the input to the models was reshaped as (4).

$$X_{\mathrm{rsae}} \in R^{n \times m \times 1} \qquad (4)$$

This format allowed CNNs to perform convolutional operations across the spatial dimensions of the features, while LSTMs and GRUs captured temporal dependencies in the sequence of features. The dataset was evaluated using a stratified 10-fold cross-validation scheme to ensure robust and unbiased assessment of model performance. Stratification ensured that the proportion of tsunami and non-tsunami classes in the target variable was preserved across each fold. For a given fold k, the dataset was split into training and testing subsets, denoted as $\{X_{\mathrm{tan}k}, y_{\mathrm{tan}k}\}$ and $\{X_{\mathrm{ts},k}, y_{\mathrm{ts},k}\}$, respectively as presented as (5).

$$X_{\mathrm{tan}k} \cup X_{\mathrm{ts},k} = X, \quad y_{\mathrm{tan}k} \cup y_{\mathrm{ts},k} = y \qquad (5)$$

This ensured that each model was trained on 90% of the data and tested on the remaining 10% in each fold, providing a comprehensive evaluation across all samples. The resulting preprocessing pipeline involved multiple stages, starting from data cleaning and imputation to feature scaling and target encoding, culminating in reshaping for model compatibility and implementing cross-validation. Mathematically rigorous transformations ensured that the dataset was well-prepared for training and evaluating deep learning models, thereby enabling robust and reliable tsunami prediction.

2.2. Proposed Methodology

This study employs three advanced deep learning architectures: Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), and Gated Recurrent Units (GRU) to predict tsunami occurrences based on seismic data. Each model is specifically designed to exploit unique data characteristics, enabling a comprehensive evaluation of their predictive capabilities. This section provides a detailed explanation of the architecture, configurations, training processes, and evaluation framework. CNN architecture is constructed to capture spatial patterns within the seismic data. The convolutional layers apply filters to the input tensor, producing feature maps through operations defined as (6).

$$Z_{i,j,k} = \sigma\left(\sum_{m=1}^{h}\sum_{n=1}^{w}\sum_{c=1}^{C} W_{m,n,c,k} \cdot X_{i+m-1,j+n-1,c} + b_k\right) \tag{6}$$

where $(X_{i,j,c})$ represents the input tensor, $(W_{m,n,c,k})$ is the filter, and (b_k) is the bias term. The activation function $(\sigma(x) = \max(0, x))$ introduces nonlinearity, while the max-pooling operation reduces spatial dimensions by selecting the maximum value within pooling windows as defined as (7).

$$P_{i,j,k} = \max_{(m,n)\in\text{window}} Z_{i+m,j+n,k} \tag{7}$$

The flattened output is passed through dense layers, and the final layer applies a sigmoid activation function to predict the probability of a tsunami as defined as (8).

$$\hat{y} = \frac{1}{1+e^{-z}} \tag{8}$$

where (z) is the weighted sum of inputs from the previous layer. The CNN model is optimized using the Adam optimizer, and binary cross-entropy loss is used to measure the prediction error:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \tag{9}$$

where (y_i) is the true label and $(\hat{y}_i)$ is the predicted probability for the (i)-th sample. LSTMs are designed to capture temporal dependencies in sequential data. Each LSTM unit employs gates to regulate information flow, where the forget gate determines which information to discard, the input gate decides what to store, and the output gate controls the visibility of the cell state. The operations are defined as (10) – (15).

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{10}$$
$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{11}$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{12}$$
$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{13}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{14}$$
$$h_t = o_t \odot \tanh(c_t) \tag{15}$$

where (c_t) is the cell state at time (t), and (h_t) is the hidden state. The LSTM's final hidden state is passed through dense layers for binary classification. GRUs simplifies the

LSTM structure by combining the input and forget gates into an update gate, while also using a reset gate. The update gate determines the amount of past information to retain, calculated as (16) – (19).

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (16)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (17)$$

$$\widetilde{h_t} = \tanh(W_h x_t + r_t \odot (U_h h_{t-1}) + b_h) \quad (18)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widetilde{h_t} \quad (19)$$

where (h_t) is the hidden state at time (t). To train and evaluate the models, stratified 10-fold cross-validation was employed. The dataset was divided into ten subsets, maintaining the class distribution within each fold. For each fold, the training and testing sets were defined as (20).

$$\text{Train}_k = \bigcup_{i \neq k} \mathcal{D}_i, \quad \text{Test}_k = \mathcal{D}_k \quad (20)$$

where $(\mathcal{D}_i)$ represents the (i)-th subset. Each model was trained on (Train_k) and evaluated on (Test_k), ensuring a robust assessment of model generalizability. Performance metrics were computed for each fold, including accuracy, precision, recall, F1 and ROC-AUC score as presented in (21) – (24) respectively.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (21)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (22)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (23)$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (24)$$

$$\text{ROC-AUC} = \int_0^1 \text{TPR}(f)\, d\text{FPR}(f) \quad (25)$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. Each model was optimized using the Adam optimizer with a learning rate ($\eta = 0.0005$). Training was performed for a maximum of 50 epoch with a batch size of 32. Early stopping was applied to halt training if the validation loss did not improve for five consecutive epochs. This rigorous training and evaluation framework ensured a robust and reliable comparison of CNN, LSTM, and GRU architectures for tsunami prediction.

3. Results and Discussion

This section presents the results of the experiments conducted to evaluate the performance of the proposed deep learning models: Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and Gated Recurrent Units (GRUs) on the tsunami prediction task. As presented in table 1, the performance of each model was assessed using stratified 10-fold cross-validation, and the metrics included precision, recall, F1-score, accuracy, and ROC-AUC. These metrics provide a comprehensive evaluation of the models' ability to classify tsunami-triggering earthquakes accurately. The CNN model demonstrated the highest performance among the three architectures across most metrics. The average precision for CNN was 0.5987, indicating its effectiveness in reducing false positives. The recall was 0.4680, reflecting its moderate capability to capture true positives. The F1-score, which balances precision and recall, was 0.5213, highlighting its overall strength in classification. The accuracy of CNN was

72.5%, the highest among the models, suggesting its general reliability in correctly classifying the samples. The ROC-AUC of CNN was 0.7838, demonstrating its ability to distinguish between classes effectively.

The GRU model followed closely behind the CNN, with a precision of 0.5885 and a recall of 0.4253. While its precision was comparable to CNN, its recall was lower, resulting in a reduced F1-score of 0.4819. The accuracy of the GRU model was 71.7%, slightly lower than CNN but still reflecting reasonable classification performance. The ROC-AUC of 0.7709 indicates that the GRU effectively differentiates between tsunami and non-tsunami events, albeit less consistently than CNN. The LSTM model performed the least effectively among the three architectures. It achieved a precision of 0.5465 and a recall of 0.3597. The lower recall compared to the other models indicates that LSTM struggled to identify true positives effectively. This resulted in an F1-score of 0.4126, significantly lower than CNN and GRU. LSTM's accuracy was 67.9%, reflecting its limited reliability in classification tasks. The ROC-AUC of 0.7298 further confirms its relatively weaker performance in distinguishing between classes.

Table 1. Performance Results

Model	Precision	Recall	F1-Score	Accuracy	ROC-AUC
CNN	0.598694	0.467992	0.521326	0.725	0.783763
GRU	0.588524	0.425284	0.481902	0.717	0.770898
LSTM	0.546463	0.359659	0.412628	0.679	0.729769

Comparatively, CNN outperformed GRU and LSTM across all metrics. The model's architecture, which is optimized for capturing spatial relationships, likely contributed to its superior performance in analyzing seismic data. GRU, with its ability to model sequential patterns efficiently, performed moderately well but exhibited lower recall, suggesting difficulty in identifying true positives consistently. LSTM, despite its theoretical strength in handling long-term dependencies, showed the weakest performance, potentially due to the complexity of the task and the limited temporal characteristics in the dataset. The performance differences among the models highlight the varying strengths and weaknesses of CNN, GRU, and LSTM architecture. While CNN is well-suited for the current dataset due to its focus on spatial feature extraction, GRU offers a balance between computational efficiency and accuracy. The LSTM model, which excels in long-term sequence modeling, may require further tuning or additional temporal features to perform effectively in this context. These results provide valuable insights into the applicability of deep learning architectures for tsunami prediction. The findings emphasize the importance of model selection based on the characteristics of the dataset and the specific requirements of the classification task. Future work could explore hybrid models that combine the strengths of CNNs, GRUs, and LSTMs to further enhance prediction accuracy and robustness.

4. Conclusion

This study investigated the application of three advanced deep learning architectures: Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and Gated Recurrent Units (GRUs) for predicting tsunami occurrences based on seismic parameters. The results demonstrated the varying effectiveness of these models, with CNN achieving the highest overall performance across key metrics, followed by GRU and LSTM. Specifically, CNN excelled in precision, accuracy, and ROC-AUC, highlighting its strength in spatial pattern extraction from seismic data. GRU performed moderately well, balancing computational efficiency and predictive accuracy, while LSTM underperformed due to its lower recall and F1-score, suggesting challenges in capturing the necessary temporal dependencies within the dataset. Comparative analysis revealed that CNN's ability to extract localized features made it the most effective model for this task, while GRU offered a viable alternative for scenarios requiring computational efficiency. The relatively weaker performance of LSTM indicates the need for either further optimization or additional temporal data to leverage its potential fully. These findings underscore the importance of aligning model architecture with the specific characteristics of the dataset and the classification task.

This research contributes to the growing body of knowledge in applying deep learning techniques for disaster prediction, particularly in the context of tsunami events. The systematic evaluation of CNN, LSTM, and GRU provides actionable insights into selecting appropriate architectures based on dataset properties and task requirements. Moreover, the study highlights the potential of deep learning models to enhance early warning systems, enabling more effective disaster response and mitigation strategies. Future work should focus on integrating additional features, such as real-time oceanographic data, and exploring hybrid models that combine the strengths of CNNs, GRUs, and LSTMs. These approaches could further improve prediction accuracy, robustness, and interpretability. Furthermore, expanding the scope of the study to include other related tasks, such as predicting the severity of tsunamis or estimating their impact, could offer valuable insights for comprehensive disaster management systems. By leveraging these advancements, the potential of deep learning models in improving the reliability and timeliness of tsunami predictions can be fully realized, contributing to the safety and preparedness of vulnerable communities worldwide.

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