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ADVANCED EARTHQUAKE PREDICTION: UNIFYING NETWORKS, ALGORITHMS, AND ATTENTION-DRIVEN LSTM MODELLING

*Maher Ali Rusho[1], Reyhan Azizova[2], Dmytro Mykhalevskiy[3], Maksym Karyonov[4] and Heyran Hasanova[2]

[1]Department of Engineering Management, University of Colorado Boulder, United States of America,
[2]Department of Digital Technologies and Applied Informatics, Azerbaijan State University of Economics, Azerbaijan;
[3]Department of Infocommunication Systems and Technologies, Vinnytsia National Technical University, Ukraine;
[4]Department of Computer Engineering and Information Systems, State University of Intellectual Technologies and Communications, Ukraine

*Corresponding Author, Received: 07 March 2024, Revised: 05 April 2024, Accepted: 13 May 2024

ABSTRACT: The study aims to develop an earthquake forecasting model based on Long Short-Term Memory (LSTM) networks with an embedded attention mechanism to improve the accuracy and reliability of forecasts that can be used in earthquake warning and mitigation applications. The objective is to explore and justify how this model can analytically improve the identification and interpretation of hidden patterns and anomalies in earthquake data to improve forecasting accuracy in seismically active regions such as Indonesia. The study used modeling techniques, analytical computations, and computer experimentation. The emphasis was placed on deep learning analysis to identify implicit indicators that could radically change the surveillance strategy and improve human safety. As a result, a model was built to illustrate the ability of LSTM networks with an embedded attention mechanism to improve earthquake forecasting by more accurately recognizing seismic patterns. This confirms the assumption that such networks can more effectively adapt to the identification of temporal dependencies in earthquake data. The model can detect and isolate seismic anomalies and precursors of major seismic events more effectively than standard forecasting approaches based on statistics and probability. The practical significance of the study lies in the opening of new opportunities for creating more accurate earthquake forecasting systems.

Keywords: Seismic forecasting, Deep learning, Anomaly data, Attention models, Neural architectures

1. INTRODUCTION

Earthquakes are extremely destructive natural phenomena that cause serious loss of life and significant property damage [1,2]. Being located in the zone of intense seismic activity of the Pacific Ocean's Ring of Fire, Indonesia experiences more than 90% of the world's earthquakes. This makes it one of the most earthquake-prone countries in the world. Indonesia often experiences loss of life and property caused by seismic activity [3-6]. This leads to significant social and economic impact, creating an urgent need for accurate earthquake forecasting.

In today's environment, the research relevance is further determined by the continuous development and progress of machine learning and artificial intelligence technologies. These innovative technologies generate powerful algorithms that can be applied to data sets to recognize hidden patterns and correlations. This opens up new possibilities for understanding and predicting various processes, including earthquakes. Neural networks, such as Long Short-Term Memory (LSTM) (Fig. 1), stand out among other machine learning technologies due to their ability to process and understand temporal sequences of data.

The attention mechanisms implemented in the LSTM networks enable the system to concentrate on the most relevant data elements, which improves the accuracy of forecasts [7]. These technologies have already proved to be effective tools in other areas of complex forecasting, including time series forecasting in finance, economics, weather, and other fields. In the case of earthquake forecasting, they can make a significant contribution by providing high accuracy and reliability of forecasts, which can help reduce risks and minimize losses.

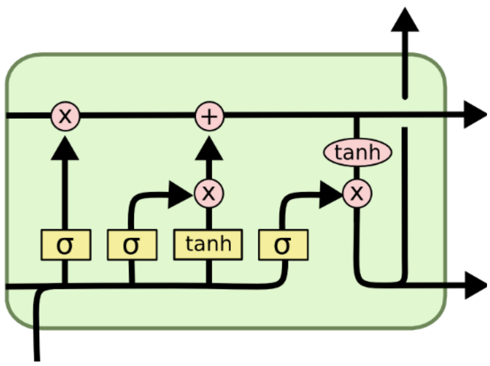

Fig.1. Long Short-Term Memory

The study by Apriani et al. [8] proposed an alternative methodology for determining earthquake magnitude based on machine learning for an early warning system. The researchers used data on seismic activity in Indonesia and developed a model based on a deep neural network (DNN) and a Random Forest (RF) machine learning algorithm. The results of statistical analysis showed that waveforms can be modelled using DNN models. Murti et al. [9] presented a proposal for multi-class earthquake detection using machine learning algorithms that can distinguish between vibrations caused by earthquakes and vibrations generated by other sources, including vandalism. Machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Artificial Neural Network (ANN) were used to develop the most efficient multi-class earthquake detection algorithm.

Wibowo et al. [10] proposed a new model for an early warning system for earthquakes in East Java, Indonesia. To determine the hypocenter and magnitude of an earthquake, the authors use the Ncheck noise processing algorithm and a deep learning-based multiobjective regression method. Wijaya et al. [11] proposed an artificial intelligence-based earthquake prediction model to mitigate the effects of seismic activity in Indonesia. The model, developed using a random forest algorithm, was trained on earthquake data recorded in Indonesia from January 1900 to January 2022. In recent years, due to the development of machine learning and artificial intelligence technologies, it has become possible to create more complex and accurate forecasting models. In this context, the study aims to create a forecasting model for earthquakes based on LSTM neural networks with an embedded attention function to improve the accuracy and reliability of forecasts.

The paper is structured to systematically explore the application of LSTM neural networks for earthquake prediction. In the introduction, the authors provide an overview of the seismic activity in Indonesia, emphasizing the critical need for advanced forecasting methods due to the country's high susceptibility to earthquakes. The Materials and Methods section details the theoretical modeling of the LSTM network, analytical calculations, and the preprocessing of the earthquake dataset for LSTM analysis. In the Results section, the effectiveness of the LSTM model is demonstrated through its ability to predict real earthquake events accurately, minimizing false alarms while recognizing a majority of seismic activities. The Discussion elaborates on the superiority of the proposed LSTM model over traditional methods. The Conclusion summarizes the LSTM model's advantages in handling long-term data dependencies for earthquake prediction and suggests directions for future research.

2. RESEARCH SIGNIFICANCE

The research holds significant implications for earthquake prediction by showcasing the effectiveness of LSTM networks in modeling temporal dependencies and detecting hidden patterns in earthquake data. It underscores the superiority of LSTMs over alternative methods, with the added advantage of the attention mechanism enhancing their predictive accuracy. While LSTMs excel in handling long-term data dependencies, there are still challenges like the “time gap problem” and the need for extensive data.

3. MATERIALS AND METHODS

The research design was based on a set of methodological approaches, including modelling, analytical calculations, and computer experimentation. Modelling methods were used to develop a theoretical model of an LSTM network with an attention mechanism capable of predicting earthquakes. The model is based on standard analytical methods used to mathematically formalize the principles of LSTM networks and create an algorithm for identifying and interpreting hidden patterns and anomalies in earthquake data.

Two main types of data were used in the study. Seismological data is information about earthquakes that have occurred in Indonesia over a while. Tectonic data describes the structure and dynamics of the earth’s crust in Indonesia. The data is compiled from information on earthquakes in Indonesia (Fig. 2) and surrounding areas over 20 years. Information on 20,622 earthquakes is included.

Fig.2. Earthquakes in Indonesia

Given that Indonesia is one of the most seismic zones in the world, the sample contains data on earthquakes of various sizes and intensities. The dataset contains the following key attributes for the development and training of LSTM networks with an attention mechanism: earthquake epicenter coordinates, focal depth, earthquake magnitude and time of occurrence. The data used for this study were obtained from the comprehensive catalogue of the USGS Advanced National Seismic System (ANSS)

[12]. The data were collected as part of an analysis of Indonesian seismic activity and offered free access to detailed and thoroughly verified earthquake information [13]. Only earthquakes that occurred on the territory of Indonesia or in the immediate vicinity are considered. Only events with a magnitude of 4.6 and above are included in the sample. This threshold allows to focus on events that have the greatest impact on the public and infrastructure. All earthquakes had to have complete and accurate data on all necessary parameters – geographical coordinates, time, depth, and magnitude. Лey metrics were used in this study to evaluate the quality of the earthquake prediction model: accuracy, completeness, and F1-measure. The metrics were calculated using a deferred test sample with the help of specialized statistical methods and tools of the Python library scikit-learn.

4. RESULTS

For effective use in LSTM networks, this dataset of earthquakes in Indonesia has been carefully processed and prepared. The data were structured in a time series format, which is especially convenient for analysis by LSTM networks and allows capturing dependencies in the dynamics of earthquakes. It is important to emphasize that the time series show nonlinear and complex patterns, which is ideal for analysis by LSTM networks. To fully predict earthquakes, four key parameters need to be determined: the expected magnitude of the earthquake, the estimated time of its onset, the spatial location of the epicenter, and the probability of the forecast being realized [14]. In addition to tracking the key parameters, earthquake data were also processed to identify numerical and categorical variables that included time intervals between consecutive earthquakes and analyzing historical seismological data. Considerable efforts were made in the pre-processing of earthquake data in Indonesia. Numerous experiments were conducted in the process of tuning the earthquake data model, which resulted in the optimal preprocessing scheme (Table 1).

To achieve maximum accuracy in earthquake prediction, the numerical data attributes were normalized using the Min-Max method. This process of levelling the scales of numerical data leads to a situation where all attributes are in the same range, which is important because LSTM networks are sensitive to feature scaling and by bringing them to a single scale, the dominance of some features over others are minimized. All earthquakes were chronologically ordered, which made it possible to accurately track and analyze the dynamics and relationships between individual earthquakes. As for the categorical attributes, they were transcoded into a format suitable for training the LSTM system.

This enhancement increases the ability to recognize important temporal patterns and sequences, resulting in improved earthquake prediction accuracy. The ‘Timestep’ column did not require any additional training, as it represents sequence numbers that define the sequence of earthquakes in time and serves to organize the data. The time of each earthquake (Timestamp) was presented in the Unix Timestamp format, which reflects the number of seconds that have passed since 1 January 1970, which simplifies the processing and presentation of temporal data. The latitude and longitude coordinates of each earthquake (Latitude_Scaled and Longitude_Scaled) were scaled using the StandardScaler tool from the scikit-learn library to improve the model training results on this data. The earthquake depth attribute (Depth_Scaled) was also scaled using StandardScaler. The magnitudes of each earthquake (Magnitude_Scaled) and the magnitude of the previous earthquake (Previous_Magnitude_Scaled) were scaled and added to the model as a new feature to improve the accuracy of the predictions. The earthquake mechanisms (Mechanism_Category) were converted to numerical values using the Label Encoding technique to facilitate model training. The model is based on recurrent neural networks LSTM. The main difference between LSTMs and standard recurrent neural networks (RNNs) is that they have gates (Fig. 3).

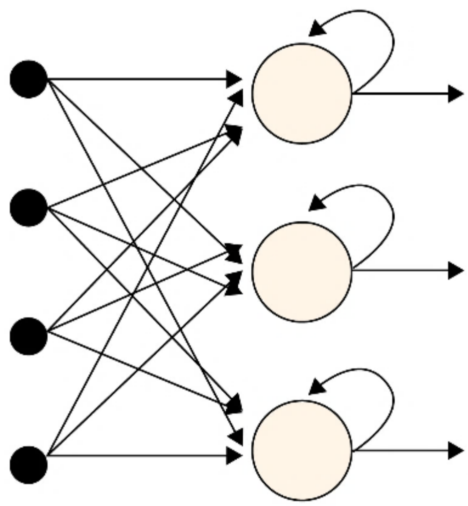

Fig.3. Recurrent neural networks

The LSTM network, or LSTM Network, was specifically designed to handle time series forecasting tasks, considering long-term dependencies in the data due to its ability to remember and use information from previous time steps [15]. The key elements of LSTM are the input, forgetting, and output gates, which determine what information should be stored, forgotten, or used at each time step. The state of each LSTM level includes not only the output but also its current state, which is updated at each time step and allows for the creation of long-term memory [16].

Table 1. Complex dataset

Timestep	Timestamp	Latitude_Scaled	Longitude_Scaled	Depth_Scaled	Magnitude_Scaled	Previous_Magnitude_Scaled	Mechanism_Category
0	631152000	-0.6	-0.12	0.6	1.2	N/A	1
1	631243200	-0.55	-0.08	0.6	1.1	1.2	1
2	631334400	-0.5	-0.05	0.52	0.9	1.1	2
3	631425600	-0.57	-0.15	0.7	0.85	0.9	1
4	631516800	-0.66	-0.2	0.5	0.79	0.85	2

The attention mechanism works in the following way: it assigns weights to each element of the input data that correspond to their "importance" for the final forecast. These weights are used to generate the context vector for the current forecast step. The context vector is a weighted sum of the inputs, where contribution of each input element to the final result. In the study, the attention mechanism is used in combination with LSTM layers to process the input data. This approach optimizes the learning of complex dependencies and circumvents the problem of gradient decay commonly encountered in recurrent neural networks. The attention mechanism significantly improves the quality of model predictions and allows the structural and meaningful combination of high-level properties of the neural network architecture, specific training algorithms, and input data modelling [17,18].

After processing the data with LSTM and using the attention mechanism, the data is transferred to the full connection layers. In these layers, each neuron has connections to all its predecessors, which allows it to integrate all the information accumulated in the previous stages of the model. During processing in this layer, each neuron performs a scalar product of its inputs and weights, adds a bias, and applies an activation function. A new value is generated at the output, which is fed to the next stage or, in the case of the final layer, becomes the final output of the model. In this model, Rectified Linear Unit (ReLU) is used as an activation function (Fig. 4).

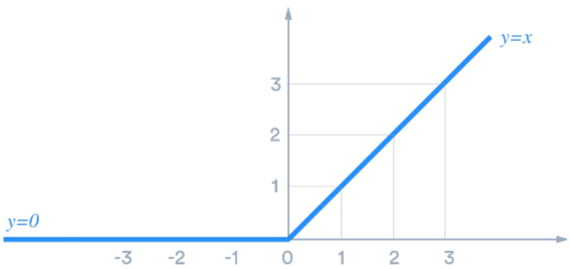

Fig.4. Rectified Linear Unit (ReLU)

This function speeds up training due to its high computational efficiency and ensures efficient distribution of gradients, keeping them unchanged when the input signals are positive. In the case of negative activation, ReLU reduces them to zero, which allows for filtering out unnecessary signals. The monotonicity and unlimited activation of ReLU preserve the sequence of input values and do not impose an upper limit on the output. The use of full connectivity layers after LSTM and the attention mechanism ensures deep data processing and the formation of a balanced prediction. At the end of the workflow, the data passes through an output layer. This layer provides the final calculations and generates the final predictive score. In the model architecture, the SoftMax function was chosen to perform the classification task as the output layer activation function (Fig. 5).

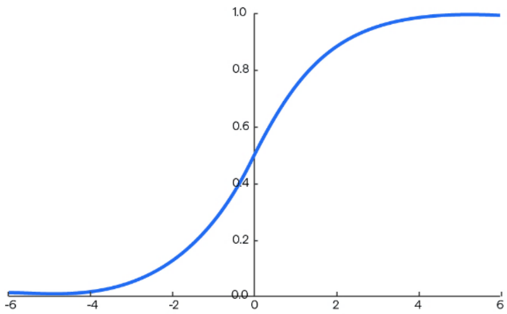

Fig.5. SoftMax function

The main advantage of this function is that it converts a set of numbers into a probability distribution, which makes the model's performance more interpretable. The number of neurons in the output layer corresponds to the number of classes in the classification task so that each neuron can generate a probability of a particular class, and the sum of such probabilities for each sample is equal to one, which facilitates interpretation. Thus, the final predictive model used in the study effectively combines the advantages of the recurrent LSTM architecture, attention mechanism, full-connection layers, and SoftMax output activation for accurate and interpretable class prediction.

The sample was divided into training, validation, and test samples in the ratio of 70:15:15. In the course of the study, the prepared sample was divided into training, validation and test samples in the ratio of 70:15:15. 70% of the total data was used to train the model – this is the main dataset on which the model was trained to recognize patterns and regularities typical of earthquakes. The remaining 15% of the data was used as a validation sample. This data set was used to fine-tune the model parameters and regularly check its performance during the training process. The validation set helps to guide the training process to avoid overfitting and to make sure that the model generalizes the learned patterns and does not just "memorize" the training set [19]. The remaining 15% of the data was set aside for post-training testing and evaluation of the model's performance. This sample is critical because it allows to assess how well the model will cope with new data that it has not seen before. The model training was an iterative process that optimized neuron weights and eliminations based on the data (Table 2).

Table 2 Iterative training process for LSTM network

Stage	Description
Initialization	Neuronal weights are initialized with random numbers to start the training process
Training	Neuronal weights are continuously adjusted to minimize the overall loss estimate calculated from the loss function for the provided data
Loss estimation	The loss function measures the disparity between the actual data and the model predictions, providing a metric for the effectiveness of the model
Prediction	The learning model predicts outcomes based on the current state of neuronal weights, allowing evaluation of the model's performance
Back-propagation	The back-propagation algorithm calculates gradients, indicating the direction and magnitude of weight adjustments necessary for minimizing loss
Optimization (Adam)	The Adam optimizer utilizes the calculated gradients to update neuronal weights, guiding the model towards improved performance
Sequence training	The LSTM network is trained on sequential data, establishing relationships between current and past data points, crucial for capturing temporal dependencies

To prevent overfitting, the study used the technique of controlling the model parameters, or "early stopping" [20]. The learning rate was controlled by feedback at each training epoch, and as soon as it became apparent that the model was no longer significantly improving its results on the validation sample, training was interrupted. The checkpoint function was used to preserve the best performance of the model at each training epoch. It automatically saves the model parameters that lead to the best results on the validation data. This enables the best model to be loaded and used for evaluation on the test dataset. To increase the training capacity of the model and further improve its classification ability, a data augmentation technique was used. It involves creating new synthetic training examples by applying various random transformations to existing training examples.

The model was tested on a deferred sample of data that the model had not seen during training. The model used its trained architecture and parameters to predict the seismic activity classes of this data. The model's predictions were then compared to real-world values to assess accuracy. The metrics were calculated using a deferred test sample with the help of specialized statistical methods and tools of the Python library scikit-learn.

The test results showed that the model correctly classified 90% of all earthquakes. This means that for the most part, the model correctly predicts seismic activity. In addition, in 88% of the cases where an earthquake occurred, the model correctly guessed it. This confirms that the model does a good job not only of correctly identifying earthquakes but also of dealing with the tricks of false alarms. Overall, this gives an overall impression of the model's success, with 89% balanced performance in combining these two aspects confirmed (Fig. 5).

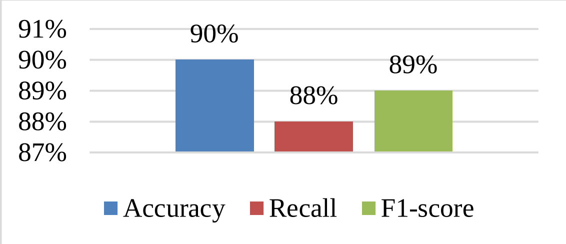

Fig.5. Earthquake prediction model quality metrics

The results obtained indicate the high quality of the model in earthquake prediction, which emphasizes the effectiveness of the architecture described in this study. The model proves to be capable of identifying real earthquake events with a minimum of false alarms. At the same time, it effectively recognizes the majority of real seismic events, reducing the risk of not detecting a real threat. The overall performance of the model demonstrates its balance and stability, providing a high ratio of accuracy and completeness in predictions.

5. DISCUSSION

The earthquake forecasting method developed in this study based on LSTM with an integrated attention mechanism demonstrated high accuracy and reliability of forecasts. The results of the analysis show a significant improvement in the quality of earthquake forecasts using the proposed approach. LSTMs with an attention function help to reveal key differences in the data and detect hidden patterns and anomalies. Johnson et al. [21] used Google's machine learning platform, Kaggle, to run an earthquake prediction competition based on data from laboratory tests. They used innovative strategies, including scaling the fracture time as a fraction of the seismic cycle and comparing the distribution of the input data for training and testing. Al Banna et al. [22] presented a model of earthquake prediction based on a bidirectional long-term memory network (Bi-LSTM) with an attention mechanism. The LSTM is used to build this model because of its long-term memory capability. The model was trained on seismic data from the Bangladesh earthquake catalogue and showed an earthquake prediction accuracy of 74.67%. In addition, a regression model was developed to predict the earthquake epicenter as a distance from a given point. Both methods proposed in these two studies have their strengths.

Chittora et al. [23] conducted an experimental analysis of earthquake prediction using machine learning classifiers, approximation curves and neural modelling. The study used six different machine learning classifiers on six datasets from different regions of India to predict the early impact of earthquakes. The results showed that the XGBoost Tree classifier often showed the best accuracy. The study provides a broader approach by applying different types of classifiers on different datasets from different regions. Wang et al. [24] also use LSTM neural networks to predict earthquakes, confirming the potential of this approach. Their early warning system detects destructive S-waves from initial P-waves and issues warnings at the onset of strong shocks. This deep learning approach creates a highly nonlinear neural network and calculates the probability of an alert at each time step. Using test data from three recent earthquakes, the LSTM network showed 0% missed alarms and 2.01% false alarms, demonstrating encouraging results.

Salam et al. [25] propose earthquake prediction models based on seven seismic indicators and hybrid machine learning techniques. Combinations of different machine learning techniques are used, including the color pollination algorithm (FPA), extreme learning machine (ELM) and least squares support vector machine (LS-SVM) to predict earthquake magnitude over fifteen days [26]. Based on the simulation results, the FPA-LS-SVM model outperformed the FPA-ELM, LS-SVM, and ELM models in terms of prediction accuracy. Jena et al. [27] propose an earthquake vulnerability assessment for the Indian subcontinent using a long-term memory model with LSTM. This study is the first to apply the LSTM model with appropriate geospatial information systems methods to assess earthquake vulnerability in India. The factors affecting vulnerability include land use, geology, geomorphology, fault distribution, transport conditions, and population density [28]. The results of the analysis help to identify priority regions for timely response to risks. Abri and Artuner [29] proposed LSTM-based deep learning methods for earthquake prediction using ionospheric data. The study examines the relationship between earthquakes and ionospheric parameters (especially total electron content or TEC) collected by GPS stations. Their LSTM models analyze the TEC values of recent days to classify “earthquake” days, comparing the results with classifiers such as SVM, LDA and Random Forest. Both studies confirm the power of LSTMs to process time series and predict natural phenomena but apply them to different types of data to reveal different aspects of earthquakes.

Bilal et al. [30] propose an ensemble learning model based on a stack of normalized recurrent neural networks (SNRNN) for earthquake detection. Their model uses three recurrent neural network models (RNN, GRU, and LSTM) with batch and layer normalization. After preprocessing the wave data, the RNN, GRU, and LSTM models sequentially extract a feature map. The study proposes a more complex ensemble approach using several different types of recurrent neural networks. For complex earthquake forecasts that depend on various parameters, a systematic analysis of ionospheric data, as proposed in the Abri and Artuner study, may be very appropriate. On the other hand, earthquake forecasting based on the analysis of specific seismic data, as the existing study does, may be effective for more direct and simplified forecasting scenarios.

Yousefzadeh et al. [31] presented the results of using a deep neural network to predict earthquakes in Iran. They comprehensively analyze both temporal and spatial parameters, unlike many studies that focus mainly on temporal parameters. In addition, they introduce a new parameter, Fault Density, and demonstrate its effectiveness for predicting large-magnitude earthquakes [32]. Both approaches confirm the importance of using spatial and temporal data for earthquake forecasting. For a more comprehensive analysis of the various factors affecting earthquakes, the approach proposed by the study could be extremely useful. For studies focused on analyzing patterns in seismic data, the use of LSTM, as in any study, may be more appropriate [33]. The current study, along with other research, confirms the significant potential of LSTM and other deep-learning methods in geophysical science and earthquake prediction. Despite the limitations and difficulties identified, the current results have already had a significant impact on the development of the field and confirm the potential for further efforts.

6. CONCLUSION

1. The model achieved a 90% accuracy rate in classifying all earthquakes, indicating a high level of precision in its predictions.

2. For cases where an earthquake occurred, the model accurately predicted the event 88% of the time, demonstrating its effectiveness in recognizing actual seismic activities.

3. The balanced performance of the model was assessed at 89%, showcasing its capability to

accurately predict earthquakes while minimizing false alarms.

4. The use of LSTM networks with an embedded attention mechanism contributed significantly to the model's ability to capture complex temporal dependencies, enhancing its forecasting accuracy.

5. Early stopping, checkpoint functions, and data augmentation techniques were instrumental in optimizing model training, preventing overfitting, improving the model's generalization on unseen data.

In future research, it is necessary to deepen the analysis of the application of LSTM and the attention mechanism to improve the accuracy of earthquake forecasting. Promising areas for further research include combining LSTM with other deep learning methods such as GRU or bidirectional networks. In addition, factors such as population density, geomorphology, or other social and technical parameters can be incorporated into models to improve the quality of earthquake forecasts.

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