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Flood Probability Prediction Based on xLSTM

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Abstract

Flood disasters occur frequently and pose significant threats to human life and property, making flood forecasting essential for disaster prevention and mitigation. This paper proposes a probabilistic flood occurrence prediction model based on the extended Long Short-Term Memory (xLSTM) network. Leveraging multi-source time-series data such as historical rainfall, flow rate, and water level, the model captures temporal features associated with flood events and predicts future flood risks in probabilistic terms. Empirical analysis on multiple benchmark flood datasets demonstrates that the xLSTM model outperforms traditional models such as LSTM and GRU in terms of prediction accuracy and generalization capability. The proposed approach shows strong application potential and practical value, providing timely and accurate flood forecasts to support effective flood risk management.

Keywords: xLSTM; LSTM; Flood Prediction; Pearson Correlation Coefficient

1. Introduction

Amid escalating global climate change, flood disasters have exhibited a trend of nonlinear intensification. A notable example is the compound flood event in June 2023, where 15 major rivers in China simultaneously exceeded warning water levels, underscoring the limitations of traditional hydrological models in forecasting extreme events (Panahi, et al, 2021). The field of flood prediction currently faces a dual challenge: on one hand, conventional statistical models, constrained by the Markov assumption, struggle to capture the intrinsic long-term dependencies of hydrological systems; on the other hand, traditional machine learning approaches, such as support vector machines, though adept at modeling nonlinear relationships, fall short in effectively representing temporal dependencies within hydrological time series (Avand et al, 2022).

As a special type of recurrent neural network, the Long Short-Term Memory network (LSTM) can effectively handle the long-term dependence problems in time series data and has shown great potential in the field of flood prediction (Chen et al, 2007). However, the traditional LSTM has certain limitations in aspects such as storage decision-making, storage capacity, and parallelization ability. In recent years, new variants such as xLSTM, mLSTM, and sLSTM have emerged. xLSTM overcomes many limitations of the traditional LSTM through improvements such as exponential gating, advanced memory structure, residual connections, and a parallelizable architecture. mLSTM expands vector operations into matrix operations, significantly enhancing the memory capacity and parallel processing ability (Zhou et al, 2022). sLSTM, on the other hand, adds a scalar update mechanism to achieve fine-grained gating control. Although these new models have achieved certain results in other fields, their application research in the direction of flood prediction is still in its infancy. This paper aims to deeply explore the performance of xLSTM, mLSTM, and sLSTM in flood prediction, provide more effective technical support for the field of flood prediction, and contribute to enhancing the ability to defend against flood disasters. Research findings have shown that the organic integration of deep learning methods and traditional hydrological models represents an effective approach to enhancing the accuracy of flood prediction under complex conditions. This integration holds significant practical implications for the advancement of the construction of digital twin river basins (Yariyan et al, 2020).

2. Related Work

Flood probability forecasting is a pivotal research domain focused on enhancing the precision and dependability of flood predictions, thereby informing effective flood management strategies. Over the years, diverse methodologies have been developed, each offering unique insights and techniques. Jörg Dietrich et al (2008) introduced an innovative approach that integrates deterministic stage forecasts from support vector regression with a probability distribution of forecast errors derived from fuzzy inference models. This method was validated through flash flood events in the Lang-Yang River, demonstrating its practical applicability in real-time scenarios. Stefan Laeger et al (2010) emphasized the integration of various ensemble prediction systems to establish a robust flood management strategy. Their work highlighted the significance of operational meteorological ensemble predictions in generating probabilistic hydrological forecasts, applied to the extreme flood event. Robertson et al (2013) showcasing the efficacy of ensemble techniques in enhancing forecasting accuracy. In operational flood forecasting, Jafar Yazdi et al (2014) developed a framework to assist practitioners in selecting and implementing suitable probabilistic forecasting techniques. Their work responded to the Pitt Review's recommendations and showcased various successful probabilistic methods that could be effectively operationalized. Ye et al (2016) contributed by proposing a novel method for generating ensemble rainfall forecasts through post-processing numerical weather prediction (NWP) models. This approach aimed to improve short-term streamflow forecasting, with future work planned to assess its efficacy across diverse climatic conditions. Chenkai Cai et al (2019) presented a stochastic framework utilizing Bayesian inference to evaluate the performance of flood warning systems based on rainfall-runoff modeling. Their methodology provided a means to estimate uncertainty bands in model parameters, thereby enhancing forecast reliability. The utilization of ensemble precipitation forecasts was further explored by Dinh Ty et al (2020)who employed products from the TIGGE initiative to drive a distributed hydrologic model. This study underscored the importance of ensemble forecasting in improving flood prediction capabilities. Wenhua Wan et al (2021) advanced the understanding of uncertainty in precipitation forecasts by proposing a model that integrates fuzzy probability and Bayesian theory. Their research assessed forecasts from multiple global weather centers, providing valuable insights into precipitation prediction reliability during flood seasons.

Existing flood probability forecasting methods, such as SVR, Bayesian inference, fuzzy logic, and ensemble predictions, have shown effectiveness but generally suffer from limited feature extraction capabilities, poor generalization, low real-time performance, and high dependency on external meteorological models. In contrast, xLSTM offers enhanced temporal modeling and automatic feature learning, enabling it to efficiently process complex, multi-source hydrological data. It significantly improves prediction accuracy and robustness, while also providing strong scalability and real-time applicability, demonstrating clear overall advantages.

3. Model Introduction

LSTM (Long Short-Term Memory Network) is an improved recurrent neural network with the addition of a memory unit, which mainly consists of a cell state and a gating mechanism (Ning et al, 2021). The cell state is responsible for preserving and transmitting historical information during the processing of sequential data, and the gating mechanism is mainly responsible for controlling the inflow, storage, and output of information to better capture long-distance dependencies.

In the figure, represents the cell state (memory state) at time step , is the input information, is the output value of the neural network unit at time step ,is the output value of the forget gate structure at time step , is the output value of the input gate structure. at time step , is the output value of the output gate structure at time step , denotes the sigmoid function, is the cell state at time step t, is the output value of the neural network unit at time step . In order to prevent excessive memory from affecting the neural network's processing of current inputs, we should selectively forget some of the components in the previous unit states, while retaining others for continued use at the current moment. The forgetting gate can determine how much information is retained for the neural network memory cellsat time , By performing operations onand , and then passing the result through the sigmoid function, the forget gate generates a vector with values ranging from 0 to 1. A value of 0 in the vector corresponds to the information that needs to be forgotten, while a value of 1 indicates the information that should be retained. The expression of the forget gate is as follows:

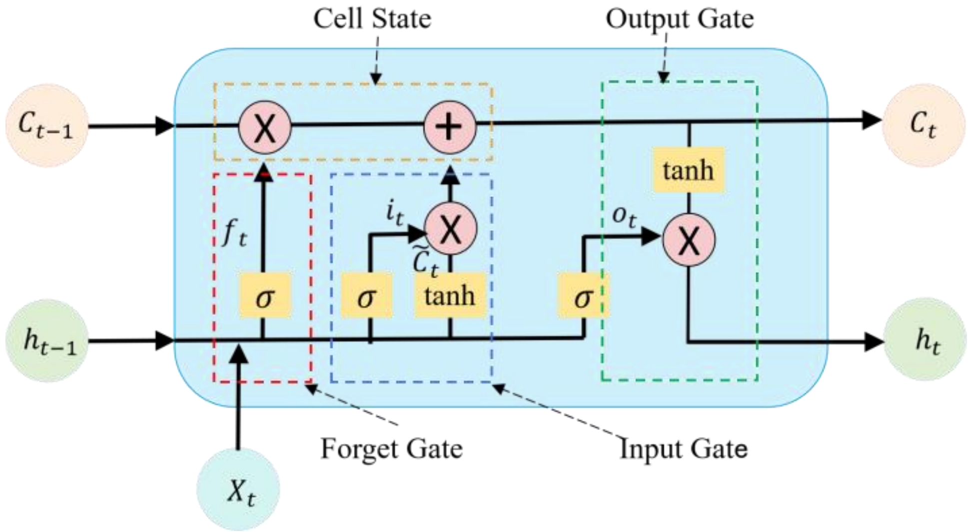

Figure 1. LSTM architecture

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f) \tag{1}$$

In Equation (1), W_f represents the weight of the forget gate, b_f is the bias term.And σ is the sigmoid function. The input gate determines how much of the input information at time step t should be retained in the current state of the neural network unit, effectively controlling the information that needs to be updated at the current time step(Yuan et al, 2025). The input quantity $X_t$and the output quantity h_{t-1}through the input gate i_t.Then, by combining the input quantity X_t and the output quantity h_{t-1} and passing them through a tanh function. $\widetilde{C}_t$ a new control parameter is created.The expressions of the input gate are as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i) \tag{2}$$

$$\widetilde{C}_t = \tanh((W_c \cdot [h_{t-1}, X_t] + b_c) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{4}$$

In Equation 4, the cell state $C_{t-1}$is updated as C_t,W_i is the weight of the input gate.The output gate C_t determines which information in the current cell state is output to h_t, X_t andh_{t-1} pass through the output gate to determine the scope of the output information.Then, Then, by combining with the partial memory information selected by the tanh function applied to C_t, h_t is determined through the output gate, The expressions of the output gate are as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

In Equations (5) and (6),,W_o represents the weight of the output gate.

SLSTM is an improved version of LSTM. SLSTM introduces exponential gating, normalization and standardization operations to enhance stability and performance (Tian et al, 2024). The exponential activation function enables the model to flexibly control the flow of information during memory and forgetting. The standardized operation state sums the product of the input gate and all subsequent forget gates to stabilize the numerical calculation during model training. In addition, SLSTM also supports multiple storage units and allows memory mixing through recurrent connections, establishing a new memory mixing method (Lin et al, 2024).

In order to further increase the memory capacity, MLSTM changes the storage unit of LSTM from scalar to matrix. This change increases the storage capacity and expression ability of the model. In addition, MLSTM also introduces two innovations, parallelization capability and covariance update. One of the defects of LSTM is that it relies on the sequential calculation of time steps and cannot be parallelized. However, MSLTM achieves parallel training by eliminating the hidden connections between time steps. Since the memory in mLSTM is expanded to matrix form, the model is allowed to store multiple key-value pairs. In order to effectively manage and update these key-value pairs, an update mechanism similar to the covariance matrix is introduced to improve the retrieval ability of rare information (Lin et al, 2024).

XLSTM(Alharthi & Mahmood, 2024). integrates SLSTM and XLSTM into the residual block structure to form an XLSTM block, which forms a more complex architecture through residual stacking, similar to Transformer, further improving the scalability of the model.

4. Tataset and Experimental Analysis

4.1. Dataset Description

The dataset used in this study contains multiple variables related to geography, environment, socioeconomic factors, and policy planning. The aim is to explore the impacts of these factors on a specific target variable (such as hs_prediction). The dataset is organized in tabular form, with each row representing an observation sample and each column representing a variable, covering multiple dimensions of information, such as terrain (dixing), climate (qihou), forest coverage rate (senlin), urbanization level (city), population (person), and relevant policies (zhengce). The comprehensive consideration of these variables helps to comprehensively understand the change trend of the target variable and its driving factors (Fu et al, 2016).

Before conducting in - depth analysis, necessary preprocessing operations were performed on the dataset to ensure data quality and the effectiveness of the analysis. A preliminary inspection revealed that there were some missing values in the dataset. Different strategies were adopted for handling missing values according to the nature of the variables and the degree of missingness. For variables with fewer missing values, they were filled using the mean or median value. For variables with a large number of missing values and a significant impact on the analysis, after considering their contribution to the overall data, they were carefully removed to avoid introducing excessive bias.

In this study, we used the corr() method in the Pandas library to calculate these correlation values. The corr() method is used to calculate the correlations between all columns in a DataFrame and returns a correlation matrix. Here, we are only concerned with the correlations with the flood probability column. The specific correlations of various influencing factors with it are shown in Figure 2 below.

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Figure 2. Heat map of various parameters

As can be seen from Figure 2 above, policies have the closest correlation with the probability of flood occurrence, followed by wetland loss, drainage systems, etc. The impact of monsoon intensity and the coastline on the probability of flood occurrence is the smallest, with values of only 0.036 and 0.048 respectively.

The Pearson correlation coefficient is a statistical indicator used to measure the strength and direction of the linear relationship between two variables. Its value ranges from -1 to 1. Specifically, 1 indicates a perfect positive correlation; -1 indicates a perfect negative correlation; and 0 indicates no linear correlation.

4.2 Experimental Analysis

The development tool selected for this paper is PyCharm, with the programming language Python 3.11.0. The Graphics Processing Unit (GPU) used is the NVIDIA GeForce GTX 4060, and the Central Processing Unit (CPU) is the i7-13600H, with 6GB of video memory. The experiment is based on a simulation-generated dataset for prediction, where the dataset is divided into 80% training data and 20% testing data for offset prediction.

The dataset used in this experiment contains multiple flood-related features, such as terrain, rivers, forest cover, urban development, climate, dam quality, and corresponding flood prediction indicators (hs_prediction). The data was cleaned to remove missing values and outliers to ensure data quality. In order to make the data meet the model input requirements, the features were standardized and mapped to the [0, 1] interval. At the same time, the dataset was divided into 70% training set and 30% test set to evaluate the generalization ability of the model.

First, the LSTM model was selected: As the basic model, LSTM effectively solves the gradient vanishing problem of traditional recurrent neural networks (RNNs) through a gating mechanism and can learn long-term dependencies in time series. In this experiment, a model structure with 1 LSTM hidden layer and 1 fully connected output layer was built. SLSTM model: Based on LSTM,

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SLSTM increases the depth of the model by stacking multiple LSTM layers, thereby enhancing the model's learning ability for complex data features. In the experiment, a 2-layer LSTM stacked structure is constructed, and each layer can extract data features from different levels. MLSTM model: MLSTM introduces multiplication operations to improve the gating mechanism of LSTM, so that the model can more flexibly capture complex nonlinear relationships and feature interactions in the data. Similarly, a model with 1 LSTM hidden layer with improved gating mechanism and 1 fully connected output layer is constructed. XLSTM model: XLSTM improves the processing ability of long sequence data by improving memory units and gating structure, and is more suitable for capturing long-term dependency information. This experiment builds a model with 1 XLSTM hidden layer and 1 fully connected output layer. All four models are trained using the Adam optimizer to minimize the mean square error (MSE) loss function. During the training process, the initial learning rate is set to 0.01, the batch size is 32, and the number of training rounds is 100. That is, when the loss on the validation set no longer decreases within a certain number of rounds, the training is stopped and the optimal model is saved.The comparison of the experimental results of each model is shown in Figures 3 and 4 below.

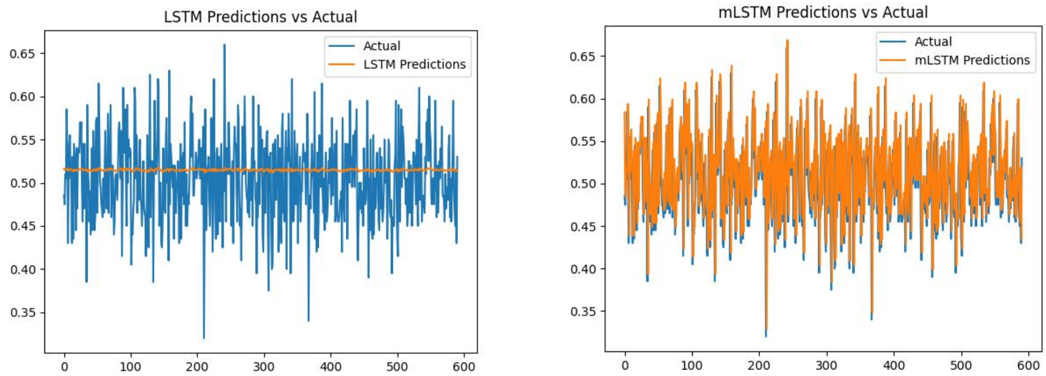

Figure 3. LSTM and mLSTM model prediction result diagram

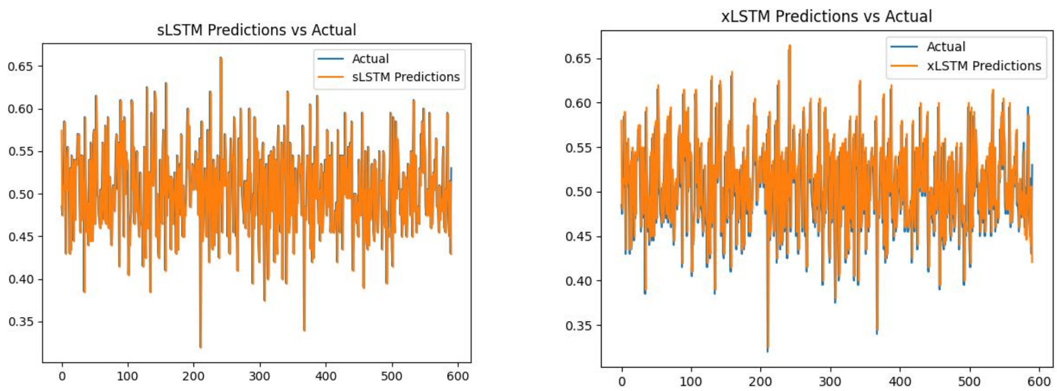

Figure 4. sLSTM and xLSTM model prediction result diagram

The mean square error (MSE) and mean absolute error (MAE) of the predicted value and the true value of the experimental results are analyzed, and it can be seen that the model has certain reliability and fit. The mean square error (MSE) and mean absolute error (MAE) of the model are shown in Table 1.

Table1. MSE, MAE and R^2comparison table

Model	MAE	MSE	R2
LSTM	0.0799	0.0124	0.0508
SLSTM	0.0530	0.0044	0.9003
MLSTM	0.0535	0.0045	0.9127
XLSTM	0.0511	0.0044	0.9307

5. Conclusions

This study focuses on the temporal characteristics of flood events and proposes a probabilistic prediction approach based on the xLSTM model. By enhancing the traditional LSTM structure with an improved gating mechanism, xLSTM more effectively models complex hydrological time-series data and improves prediction performance. Experimental results indicate that xLSTM achieves superior performance across various evaluation metrics and maintains high stability and accuracy even under complex and dynamic hydrological conditions. Future work may incorporate additional data sources, such as remote sensing and atmospheric information, to further enrich the model's input features. Moreover, integrating the proposed model into real-time early warning systems could significantly enhance its practical utility in flood risk mitigation.

Author Contributions:

Conceptualization, F.Y., R.C., G.Q.; methodology, F.Y., R.C., G.Q.; software, F.Y., R.C., G.Q.; validation, F.Y., R.C., G.Q.; formal analysis, F.Y., R.C., G.Q.; investigation, F.Y., R.C., G.Q.; resources, F.Y., R.C., G.Q.; data curation, F.Y., R.C., G.Q.; writing—original draft preparation, F.Y., R.C., G.Q.; writing—review and editing, F.Y., R.C., G.Q.; visualization, F.Y., R.C., G.Q.; supervision, F.Y., R.C., G.Q.; project administration, F.Y., R.C., G.Q.; funding acquisition, F.Y., R.C., G.Q. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest:

The authors declare no conflict of interest.

References

Alharthi, M., & Mahmood, A. (2024). xlstmtime: Long-term time series forecasting with xlstm. AI, 5(3), 1482-1495.

Avand, M., Kuriqi, A., Khazaei, M., & Ghorbanzadeh, O. (2022). DEM resolution effects on machine learning performance for flood probability mapping. Journal of Hydro-Environment Research, 40, 1-16.

Cai, C., Wang, J., & Li, Z. (2019). Assessment and modelling of uncertainty in precipitation forecasts from TIGGE using fuzzy probability and Bayesian theory. Journal of Hydrology, 577, 123995.

Chen, S. T., & Yu, P. S. (2007). Real-time probabilistic forecasting of flood stages. Journal of Hydrology, 340(1-2), 63-77.

Dietrich, J., Trepte, S., Wang, Y., Schumann, A. H., Voß, F., Hesser, F. B., & Denhard, M. (2008). Combination of different types of ensembles for the adaptive simulation of probabilistic flood forecasts: hindcasts for the Mulde 2002 extreme event. Nonlinear Processes in Geophysics, 15(2), 275-286.

Fu, K., Hainey, T., & Baxter, G. (2016, October). A systematic literature review to identify empirical evidence on the use of computer games in business education and training. In European Conference on Games Based Learning (p.232). Academic Conferences International Limited.

Laeger, S., Cross, R., Sene, K., Weerts, A., Beven, K., Leedal, D., ... & Whitlow, C. (2010). Probabilistic flood forecasting in England and Wales–can it give us what we crave?. In Proceedings of the British hydrological society international symposium, managing consequences of a changing global environment. Newcastle.

Lin, Z., Tian, Z., Zhang, Q., Ye, Z., Zhuang, H., & Lan, J. (2024). A conflicts-free, speed-lossless KAN-based reinforcement learning decision system for interactive driving in roundabouts. arXiv preprint arXiv:2408.08242.

Lin, Z., Zhang, Q., Tian, Z., Yu, P., & Lan, J. (2024). DPL-SLAM: enhancing dynamic point-line SLAM through dense semantic methods. IEEE Sensors Journal.

Nguyen, D. T., & Chen, S. T. (2020). Real-time probabilistic flood forecasting using multiple machine learning methods. Water, 12(3), 787.

Ning, Y., Ding, W., Liang, G., He, B., & Zhou, H. (2021). An analytical risk analysis method for reservoir flood control operation considering forecast information. Water Resources Management, 35(7), 2079-2099.

Panahi, M., Jaafari, A., Shirzadi, A., Shahabi, H., Rahmati, O., Omidvar, E., ... & Bui, D. T. (2021). Deep learning neural networks for spatially explicit prediction of flash flood probability. Geoscience Frontiers, 12(3), 101076.

Robertson, D. E., Shrestha, D. L., & Wang, Q. J. (2013). Post-processing rainfall forecasts from numerical weather prediction models for short-term streamflow forecasting. Hydrology and Earth System Sciences, 17(9), 3587-3603.

Tian, Z., Zhao, D., Lin, Z., Zhao, W., Flynn, D., Jiang, Y., ... & Sun, Y. (2024). Efficient and balanced exploration-driven decision making for autonomous racing using local information. IEEE Transactions on Intelligent Vehicles.

Wan, W., Lei, X., Zhao, J., Wang, M., Khu, S. T., & Wang, C. (2021). A forecast-skill-based dynamic pre-storm level control for reservoir flood-control operation. Water, 13(4), 556..

Yariyan, P., Janizadeh, S., Van Phong, T., Nguyen, H. D., Costache, R., Van Le, H., ... & Tiefenbacher, J. P. (2020). Improvement of best first decision trees using bagging and dagging ensembles for flood probability mapping. Water Resources Management, 34, 3037-3053.

Yazdi, J., Salehi Neyshabouri, S. A. A., & Golian, S. (2014). A stochastic framework to assess the performance of flood warning systems based on rainfall-runoff modeling. Hydrological processes, 28(17), 4718-4731.

Ye, J., Shao, Y., & Li, Z. (2016). Flood forecasting based on TIGGE precipitation ensemble forecast. Advances in Meteorology, 2016(1), 9129734.

Yuan, F., Huang, X., Zheng, L., Wang, L., Wang, Y., Yan, X., ... & Peng, Y. (2025). The Evolution and Optimization Strategies of a PBFT Consensus Algorithm for Consortium Blockchains. Information, 16(4), 268.

Zhou, Y., Cui, Z., Lin, K., Sheng, S., Chen, H., Guo, S., & Xu, C. Y. (2022). Short-term flood probability density forecasting using a conceptual hydrological model with machine learning techniques. Journal of Hydrology, 604, 127255.