


Deep Transfer Learning Based on LSTM Model for Reservoir Flood Forecasting

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ABSTRACT

In recent years, deep learning has been widely used as an efficient prediction algorithm. However, this algorithm has strict requirements on the size of training samples. If there are not enough samples to train the network, it is difficult to achieve the desired effect. In view of the lack of training samples, this article proposes a deep learning prediction model integrating migration learning and applies it to flood forecasting. The model uses random forest algorithm to extract the flood characteristics, and then uses the transfer learning strategy to fine-tune the parameters of the model based on the model trained with similar reservoir data; and is used for the target reservoir flood prediction. Based on the calculation results, an autoregressive algorithm is used to intelligently correct the error of the prediction results. A series of experimental results show that our proposed method is significantly superior to other classical methods in prediction accuracy.

KEYWORDS

Autoregressive algorithm, Deep learning, Flood forecasting, Intelligent correction, LSTM, Random forest algorithm, Reservoir, RNN, Transfer learning

INTRODUCTION

Flood disasters are natural disasters with high frequency, a wide scope of harm, and a serious impact on the safety of people's lives and property. In July 2021, heavy rainfall in Zhengzhou caused a flood disaster that affected 1,844,900 people, resulting in 292 deaths and 47 missing persons, with a direct economic loss of 53.2 billion yuan (Su et al., 2021). With the rapid development of China's economy, the economic losses caused by flood disasters have become increasingly serious. The task of flood control and disaster reduction is still very arduous. As one of the important nonengineering measures for flood control and disaster reduction, flood forecasting plays a key supporting role in flood control

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and disaster reduction. Using modern information technology to develop high-precision flood forecasts can help managers adopt scientific flood-control strategies, which is of great significance to reducing the loss of people's lives and property.

Due to the influence of many factors, such as hydrology, meteorology, topography, and vegetation, flood-forecasting technology is a complex, nonlinear model. Many scholars and experts have established flood-forecasting models based on the basic principles of hydrology (Icyimpaye et al., 2022; Noymanee & Theeramunkong, 2019). However, these models usually need to set a large number of parameters, which has a great impact on the prediction results. If the model parameters cannot be accurately obtained, the expected effect will not be achieved.

With the rapid development of information technology, machine learning has been widely used in various fields. Relying on its strong generalization ability and adaptive learning ability, machine learning has also brought innovation and breakthroughs to different industries. Some scholars use machine-learning algorithms to establish water-level prediction models and apply them to flood forecasting (Ahmed et al., 2022; Wee et al., 2021). In recent years, time-series prediction modeling has been one of the key areas of academic concern. Traditional methods focus on parametric models generated by professional knowledge, while machine-learning algorithms provide a data-driven method to learn dynamic sequences (Masini et al., 2023).

With the improvement of data availability and computing power, deep learning has become the research focus of time-series prediction models (Sivakumar et al., 2022). In the learning of time-series data, the traditional recurrent neural network (RNN) has many learning bottlenecks and technical defects, while the long short-term memory (LSTM) (Sahoo et al., 2019) neural network overcomes the shortcomings of the recurrent neural network. LSTM overcomes the bottleneck of gradient explosion and gradient disappearance in the learning and training of long time series data and shows a strong ability to learn long series data (Sahoo et al., 2019).

Scholars in various fields have begun to use LSTM to predict long time series and have achieved good performance (Sagheer & Kotb, 2019). Flood forecasting, as one of the typical scenarios for temporal data prediction, has gradually attracted the attention of scholars. These studies have established a series of data-driven flood-forecasting models based on historical hydrological data (Puttinaovarat & Horkaew, 2020). The studies show that the LSTM neural network has a learning advantage for the flood process of long time series, but most of the research results are still confined to the simple comparison of network performance. In fact, deep-learning network training requires a large number of data samples; too few samples are prone to overfitting problems, resulting in poor extension of the trained neural network. Therefore, it is impossible to build intelligent models in areas lacking hydrological data. However, the application of transfer learning can effectively solve the dilemma of small-sample modeling.

To solve the above problem, this work proposes a deep-learning framework based on hybrid LSTM and transfer learning and applies it to flood forecasting. This model uses a transfer-learning strategy to pretrain the model using historical data from similar reservoirs and then fine-tune the model parameters with the latest data to achieve accurate prediction. To improve the efficiency and accuracy of the model, this work adopts the random-forest algorithm to extract flood features and uses the autoregressive algorithm to intelligently correct the prediction results. The experimental results indicate that this method has obvious advantages for reservoir flood forecasting when historical data are lacking.

RELATED WORK

Over the past decades, researchers have established traditional hydrological models based mainly on physical mechanisms or concepts for flood forecasting. Generally, these models include three types: centralized models (such as the Xin'anjiang model), semi-distributed models (such as TOPMODEL),

and distributed models (such as SWAT). However, due to their inherent mechanisms, the prediction accuracy of these hydrological models is limited.

The rapid development of computer science and new technologies related to machine-learning, data-mining, and optimization algorithms provides new opportunities for the application of machine-learning methods in the field of flood-forecasting research. Machine learning-based flood-forecasting models have gradually become a hot spot in the hydrological field (Mosavi et al., 2018). Among the existing machine-learning flood-forecasting models, support vector machines (SVM) and artificial neural networks (ANN) are the two most typical models in the field of flood forecasting (Zhang et al., 2018). SVM has shown good results in flood-forecasting research, and it can select the appropriate kernel for different research problems and then select the characteristic elements that are suitable for the research purpose to achieve the desired results (Yan et al., 2018). Wu et al. (2019) proposed a support vector regression (SVR) model for flood forecasting in mountainous areas, which has satisfactory performance in predicting peak flows one to three hours ahead. Faruq et al. (2021) proposed a SVR model for predicting flood levels in downstream regions with different lead times. Research has shown that SVR can easily predict river water levels within 1 to 12 hours before the predicted time.

The function of an ANN is similar to that of the human brain and nervous system. It has been widely used as an effective tool to reveal the nonlinear relationship between input and output. Biragani et al. (2016) applied ANN and data-fusion techniques to the mathematical modeling of flood forecasting for estimating flood discharge. Dtissibe et al. (2020) used a multilayer perceptron to design an ANN model for flood forecasting, which takes the flow as the input-output variable. Numerous experiments have demonstrated the predictive ability of the model. With the increase in research on ANN models, the limitations of ANN models have also been highlighted, such as the disappearance of local optimal solutions and gradients, which limits the application of the model.

Since 2012, deep-learning methods have attracted wide attention in academia and industry (Kao et al., 2022), and research on deep-learning methods in the field of hydrological prediction has gradually increased, such as nonlinear autoregressive neural networks (Cui et al., 2023), convolutional neural networks (Shu et al., 2021), and LSTM neural networks (Liang, 2023; Hu et al., 2019; Moishin et al., 2021). Cui et al. (2023) proposed a hybrid model for flood forecasting, which is a nonlinear autoregressive neural network with external input integrated with a data-preprocessing module and uses wavelet transform for practical sequence decomposition and multigene genetic programming for detail scaling so as to effectively solve the highly nonlinear and stochastic problems of flood forecasting.

Liu et al. (2017) proposed a deep-learning method for flow prediction by integrating stacked autoencoders (SAEs) and back propagation neural networks (BPNNs), which utilizes both SAE's strong feature representation capability and BPNN's superior prediction capability. Hui (2020) proposed a flood-forecasting model based on a convolutional neural network, adding more influencing factors to the model to improve the prediction accuracy.

In recent years, more and more scholars have attempted to use LSTM networks to solve flood-forecasting problems. Liang (2023) proposed a cycle prediction model of an LSTM neural network based on mutual information. This model overcomes the problems that the traditional model has in effectively simulating the complex relationship in the hydrological process, the current artificial neural network input and output are independent of each other, and the accuracy of medium- and long-term hydrological flow prediction is reduced so that the time-series processing ability of the LSTM neural network can be fully utilized. Moishin et al. (2021) combined the prediction advantages of a convolutional neural network and a LSTM network, constructed a hybrid depth learning algorithm to design and evaluate flood-forecasting models, and used daily lagging flood index and precipitation time-series data to determine the flood conditions of multiple prediction ranges. Hu et al. (2019) proposed a deep-learning framework integrating LSTM and reduced-order models. At the same time, the two models are used to represent the flood distribution, which improves the accuracy and efficiency of flood forecasting. The application of deep-learning technology has significantly improved the accuracy and promoted the development of flood forecasting. However, deep-learning

technology has a strict dependence on the size of data samples, and the shortage of data samples seriously affects prediction accuracy.

In contrast to the above methods, this study focuses on flood forecasting from another angle. In view of the lack of hydrological data in some reservoirs, the combination of transfer-learning technology and LSTM is used to improve the accuracy of flood forecasting.

METHODOLOGY

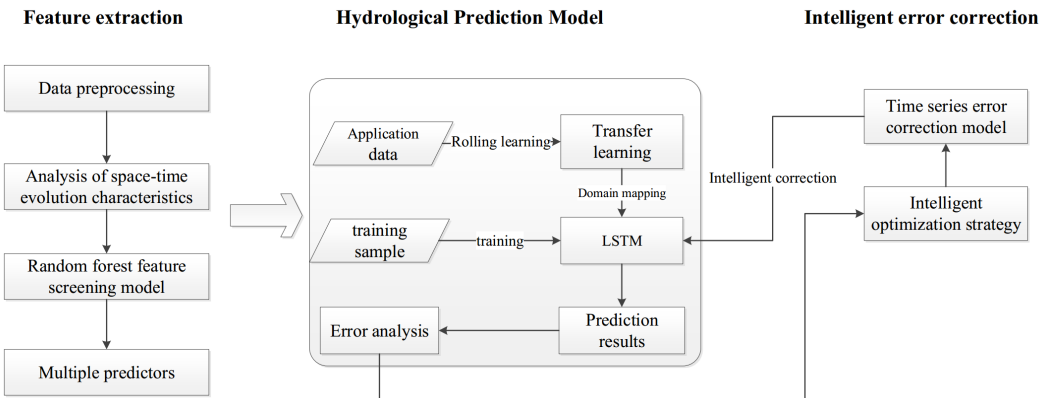
This work takes reservoir flood forecasting as the research object. Based on the collection, collation, and cleaning of historical data, the spatiotemporal evolution characteristics of multiple time scales are analyzed, and factors that contribute greatly to flood forecasting as the main fields of flood-forecasting model input are selected. Based on the LSTM neural network, the flood-forecasting model is established. On the basis of training with historical data, the transfer-learning strategy is introduced to carry out rolling learning on the applied new sample data to reduce the calculation cost of flood forecasting. A time-series error-correction model is designed, an intelligent optimization strategy is proposed, and intelligent correction of flood forecasting is realized based on error analysis and magnitude calculation. The flood forecast and intelligent correction model is shown in Fig. 1.

Flood-Feature Extraction Based on Random Forest

There are many hydrological and meteorological spatiotemporal feature elements that affect flood forecasting, many of which have no or only a small contribution to flood forecasting. The number of features has a great impact on the training time and training accuracy of the model. Therefore, it is necessary to select features that have a greater impact on the results for further modeling. This work uses the random-forest algorithm for feature screening.

The idea of the random-forest algorithm is to see how much each feature contributes to each tree in the random forest, then average it, and finally compare the contribution between different features (Cakir et al., 2021). When using random forest/CART tree, the Gini index value is generally used as the standard of the segmentation node, while in weighted random forest, the essence of weight is to assign a larger weight to small classes and a smaller weight to large classes—that is, to give a greater punishment to the small class. Suppose there are m features $\{X_1, X_2, \dots, X_m\}$. To calculate the Gini index score VTM_j of each feature X_j , that is, the average change in the node splitting impurity of the j th feature in all decision trees of the random forest, the calculation formula of the Gini index is as follows:

Figure 1. Reservoir flood forecast and intelligent correction model



$$GI_m = 1 - \sum_{k=1}^K p_{mk}^2, \quad (1)$$

where p_{mk}^2 represents the proportion of category k in node m . The importance of feature X_j at node m can be expressed as:

$$VIM_{im}^{gini} = GI_m - GI_l - GI_r, \quad (2)$$

where GI_l and GI_r represent the Gini index of the two new nodes after branching. If the node of feature X_j in decision tree i is in set M , then the importance of X_j in the i th tree is:

$$VIM_{ij}^{gini} = \sum_{m \in M} VIM_{jm}^{gini}. \quad (3)$$

Suppose there are n trees in the random forest; then:

$$VIM_j^{gini} = \sum_{i=1}^n VIM_{ij}^{gini}. \quad (4)$$

All obtained scores are normalized to obtain the importance score:

$$VIM_j' = \frac{VIM_j}{\sum_{i=1}^c VIM_i}. \quad (5)$$

Finally, based on the importance score, the characteristics of hydrological elements with greater contribution are selected as the input factors of the flood-forecasting model.

Design of Flood-Forecasting and Intelligent-Correction Model

On the basis of fully analyzing the historical data and extracting the main prediction features, the LSTM neural network is proposed to mine the nonlinear mapping relationship between the target variables and the observation data of the influence variables. Considering the contribution of the prediction results of the latest application data, a transfer-learning strategy is proposed to carry out rolling learning on the latest application data to improve the prediction accuracy without increasing computing resources.

LSTM Neural Network

The LSTM neural network is a deep-learning framework based on a cyclic neural network. The LSTM neural network can capture historical data information at a long time interval, thus solving the problem of gradient explosion of the cyclic neural network. LSTM is composed of several storage units that store information. Each storage unit realizes the protection and control of information through three special gates (input gate, forgetting gate, and output gate).

The forgetting gate f_t determines how much information of the previous cell is retained by the current cell, and its value is shown in (6):

$$f_t = \sigma(\omega_f \cdot [h_{t-1}, x_t] + b_f), \quad (6)$$

where ω_f is the weight matrix, b_f is the deviation, and σ is the sigmoid function.

The input gate controls the update of the current input data to the storage unit status value, and its value is shown in (7):

$$i_t = \sigma(\omega_i \cdot [h_{t-1}, x_t] + b_i), \quad (7)$$

where ω_i is the weight matrix and b_i is the deviation. The new status information \tilde{c}_t can be obtained from (8):

$$\tilde{c}_t = \tanh(\omega_c \cdot [h_{t-1}, x_t] + b_c). \quad (8)$$

Thus, the current status c_t can be obtained as:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t. \quad (9)$$

The output gate o_t controls the output value of the state value of the memory cell, and the value is as in (10) and (11), where ω_o is the weight matrix and b_o is the deviation.

$$o_t = \sigma(\omega_o \cdot [h_{t-1}, x_t] + b_o), \quad (10)$$

$$h_t = o_t \cdot \tanh(c_t). \quad (11)$$

With the help of three control gates and storage units, LSTM can read, reset, and update long-term information. Due to the sharing mechanism of the internal parameters of LSTM, it can be controlled by setting the weight matrix.

Transfer Learning

In recent years, machine learning has been widely used in various fields and has achieved success. Generally, there are two requirements for the data used in machine learning: one is that the data used for training and testing have the same feature space, and the other is that the data used for training and testing have the same feature distribution. Once the feature distribution of the data changes, the model also needs to be retrained. However, in practical applications, retraining the model is very time-consuming and often encounters problems such as insufficient data or lack of a large amount of labeled data, which makes it difficult to train better models. To solve the above problems, researchers have proposed transfer learning (Zhuang et al., 2020). In transfer learning, the existing knowledge is called the source domain, abbreviated as D_s , and the new knowledge to be learned is called the target domain, abbreviated as D_r . Transfer learning is learning that helps improve the prediction of the target domain by learning the knowledge of the source domain.

Given a source domain $D_s = \{X_s, f_s(X)\}$ and learning tasks T_s and given a target domain $D_r = \{X_r, f_r(X)\}$ and corresponding learning objectives T_r , when $D_s \neq D_r$ or $T_s \neq T_r$, use the source domain and the learning on the source domain to obtain the prediction function $f_t(\cdot)$ on the target domain. In this definition, the feature distribution and feature space together form a domain in transfer learning. That is, $D = \{\chi, P(X)\}$. When $D_s \neq D_r$, there are two situations: $\chi_s \neq \chi_r$ or $P(X_s) \neq P(X_r)$, where $X_s \in \chi_s$, $X_r \in \chi_r$. Conditional distribution and label space together constitute the task of transfer learning $T = \{\gamma, P(Y|X)\}$. When $T_s \neq T_r$, there are also two situations: $\gamma_s \neq \gamma_r$ or $P(Y_s) \neq P(Y_r)$, where $Y_s \in \gamma_s$, $Y_r \in \gamma_r$. When the source domain and the target domain are the same, the task target is also the same, that is, $D_s = D_r$ and $T_s = T_r$; then, this problem becomes an ordinary machine-learning task.

According to the different attributes of data and labels, the transfer-learning methods can be divided into four types. The first is that the label space is the same as the feature space; that is, the source data domain and the target data domain are different only in data distribution. The second is the difference in feature space; that is, the label space between the two domains is the same and only the feature space is different. The third is different tag spaces; that is, the feature spaces between the two domains are the same, but the tasks are different. The fourth is that the label space and the feature space are not the same. In this case, there are both different tasks and domain offsets. The problems to be solved in this paper belong to the first category.

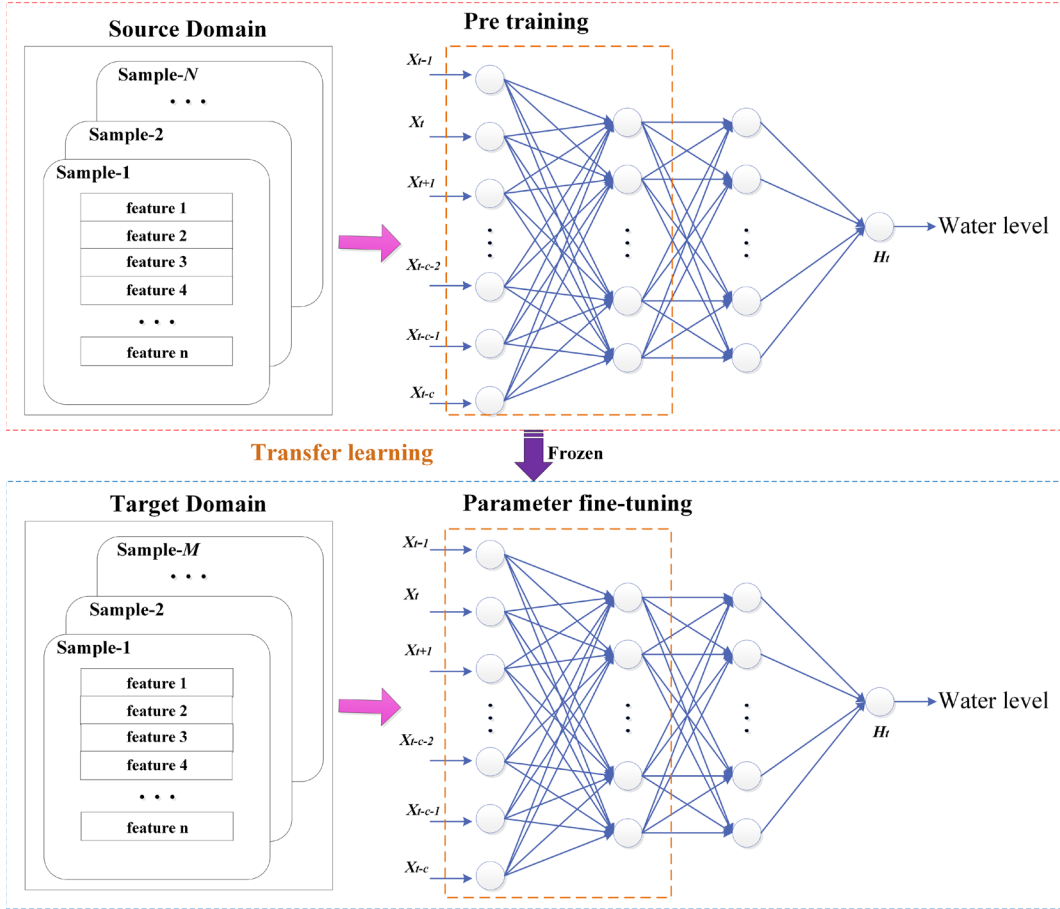
Flood-Forecasting Model

We designed a flood-forecasting model based on LSTM and transfer learning. The model framework is shown in Fig. 2. First, the parameters of the LSTM neural network are optimized by global optimization based on the sequence model to obtain the optimal network architecture and the optimization model is pretrained in the source domain. Then, the first n layers of the neural network, that is, the part shared by the source domain and the target domain, are frozen to extract the common features of time-series data in the two domains. Finally, the initialized network is migrated to the target domain and the partially frozen model is fine-tuned using the data from the target domain. The unfrozen part is retrained to optimize the model weight parameters and achieve flood forecasting. By introducing transfer learning, the model conducts rolling learning on the new sample data, continuously optimizes the weight parameters of the neural network, and improves the accuracy of the model prediction. The input layer contains $f \times c$ neurons (where f represents the number of features and c represents the time step, which represents the impact of some factors in the early stage of the reservoir on the future water level), and they receive the water-level feature data from $t-l$ to $t-c$. The number of hidden layer nodes is m , indicating the size and complexity of the hidden layer. The larger the m , the more complex the model. The output layer is a linear network layer containing only one neuron, which is used to output the predicted water level H_t at time t .

Real-Time Correction Algorithm

Real-time correction of flood forecasting involves calculating the forecast error of the hydrological forecast model in real time and correcting the model parameters, state, and forecast output value to improve the accuracy of flood forecasting. In this paper, the error autoregression model is used to correct the flood-forecasting error. The model assumes that the forecasting error has a correlation between the front and the back. According to the historical forecasting error series, the correlation is found, and then the future error is predicted to correct the original forecasting results. In operational forecasting, an error-based autoregression model is usually constructed according to the error between the measured value and the predicted value in the previous periods of the forecast. Then, according to the correction model, the error of the prediction time is calculated and added to the prediction value, which is the corrected prediction value at that time (Liang et al., 2021). The autoregressive model is calculated as follows:

Figure 2. Flood-Forecasting model based on LSTM and transfer learning



Step 1. Calculate the error sequence at the moment before the flood.

$$e_t = Q_t - QC_t, \quad (12)$$

where e_t represents the model calculation error at time t , Q_t denotes the measured flow at time t , and QC_t is the forecast flow at time t .

Step 2. Establish the functional relationship between the previous error series and the future error series.

$$e_{t+L} = c_1 e_t + c_2 e_{t-1} + \dots + c_n e_{t-n+1} + \xi_{t+L}, \quad (13)$$

where e_{t+L} represents the prediction error at time t , c_n is the regression coefficient (n is the regression order of the model, $n = 1, 2, 3, \dots$), and ξ_{t+L} represents the residual error of the corrected prediction model at time $t+L$.

Step 3. Determine the order of the autoregressive model. The stability of the autoregressive model is closely related to the model order n in the formula. In this paper, the Akaike information criterion (AIC) order determination criterion is used to determine the optimal order of the model so that the minimum value of n of AIC information is the ideal order of the model.

$$\min AIC_n = N \ln \sigma^2 + 2n, \quad (14)$$

where N is the total number of data samples and σ represents the standard deviation of the time-series samples.

Step 4. Calibration regression coefficient. This paper uses the parameter calibration method to determine the regression coefficient.

Step 5. Calculate the model-prediction correction value at the next prediction time.

EXPERIMENTS

In this section, we conduct a series of experiments on real-world datasets and compare them with some classical methods to verify the advantages of the proposed method.

Datasets

The experiment is based on real datasets of two reservoirs. As shown in Fig. 3, both reservoirs are located in the Huai River Basin, with a relatively close geographical location and similar terrain and climate conditions. The dataset of Reservoir A contains 139,582 data records, which is more than six years of historical data from July 1, 2015, to April 28, 2022. The dataset of Reservoir B contains 8,937 data records, which is the historical data of one year from July 1, 2020, to July 1, 2021. Each of the two datasets contains rainfall station monitoring data and water-level data for different periods. The field information of the database is shown in Table 1.

To study the performance of the proposed method in flood-forecasting applications, we extract features based on key indicators such as reservoir water level, inflow, outflow, precipitation during periods, daily precipitation, weather conditions, and rainfall data observed by rainfall stations. The extracted features are used as input data for the prediction model. The model output is the water level of the water-level station during different prediction periods.

Comparison Metrics

We use three commonly used performance metrics to comprehensively evaluate the proposed model, which are described as follows:

(1) RMSE (root mean square error):

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_c(i) - y_0(i))^2}{n}}. \quad (15)$$

(2) MAE (mean absolute error):

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_c(i) - y_0(i)|. \quad (16)$$

(3) NSE (Nash-Sutcliffe efficiency index):

Figure 3. Reservoir location information



Table 1. Main parameters

Attribute	Description
TM	Time
DPR	Time-period precipitation
INTV	Time period
DYP	Daily precipitation
WTH	Weather condition
RZ	Reservoir water level
INQ	Reservoir inflow
W	Storage capacity
OTQ	Reservoir outflow
RWPTN	Reservoir water potential

$$NSE = 1 - \frac{\sum_{i=1}^n (y_c(i) - y_0(i))^2}{\sum_{i=1}^n (y_c(i) - \bar{y}_0)^2}. \quad (17)$$

In the above formulas, $y_c(i)$ represents the i th predicted value, $y_0(i)$ represents the i th measured value, and \bar{y}_0 represents the average of the measured values.

Comparison Methods

To verify the advantages of the proposed method, we compared it with three classic flood-forecasting methods, which are described as follows:

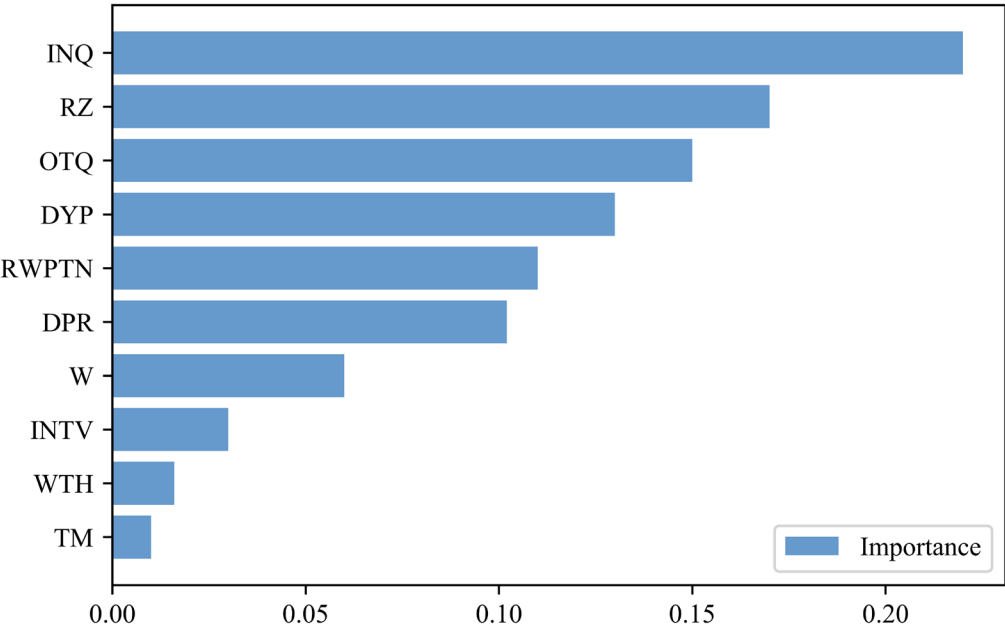
- (1) SVR. This is an important application branch of the support vector machine, which is used to realize regression algorithms and is applied to flood forecasting (Zhang et al., 2018).
- (2) LSTM. Long- and short-term memory neural network model for flood forecasting proposed by Le et al. (2019).
- (3) CNN-LSTM. A coupling model of convolutional neural network and long- and short-term memory neural network. In this model, the output of the CNN model is taken as the input of the LSTM model, and the output of the LSTM model is fully connected with the final output result (Li et al., 2022).

Experimental Results

In this section, we compare the performance of the proposed method with the three baseline methods through a series of experiments. In the experiment, we use the trial-and-error method to optimize the parameters of various algorithm models. After multiple experiments, it was found that the prediction accuracy did not significantly improve after the number of iterations exceeded 1,000. We believe that 1,000 is the optimal number of iterations. Similarly, the number of iterations for fine-tuning is 200. Therefore, in our proposed method, the number of iterations for pretraining is 1,000 and the number of iterations for fine-tuning training is 200.

Figure 4 shows the ranking results of the feature importance of reservoir floods based on the random-forest algorithm. Features of less than 0.1 importance did not contribute much to the prediction result and were no longer retained. These features are often correlated with other important features,

Figure 4. Feature importance ranking results



and their influence on the prediction results is indirect. Therefore, six other important features were used in subsequent experiments.

In the first experiment, we used different numbers of sample data to train the prediction model and selected the latest 500 data points as the test data. In this experiment, the predicted time period is set to six hours. Table 2 and Table 3 describe the RMSE and MAE performance of different methods, respectively. The RMSE and MAE of all methods decrease with the increase in the number of training samples; this means that the increase in training samples can improve the accuracy of all prediction models. Obviously, our proposed algorithm has obvious advantages. When the training sample reaches 3,000, the values of RMSE and MAE are 0.113 and 0.062, respectively, which are far superior to those of the other methods. The advantages of the proposed deep-learning framework based on transfer learning have been verified. When the training samples are small our method still performs well, indicating that historical data from similar reservoirs is helpful for model parameter training. The experimental results also demonstrate that our method can be applied to reservoir flood forecasting with less historical data.

Figure 5 shows the performance of different algorithms in the NSE. Our proposed method is obviously superior to other algorithms in NSE, especially when the training samples are fewer, and the advantages are more obvious. Compared with LSTM, the proposed method adopts the transfer-learning strategy and dynamic-adjustment strategy. Due to the lack of sufficient samples, traditional prediction methods (such as LSTM and SVR) are difficult to achieve optimal data mapping relationships. In addition, these methods lack strategies to correct prediction errors. As a result, they cannot achieve the desired results. The proposed model utilizes other reservoir data to train the model and fine-tune the model parameters with new training data, thereby improving the predictive ability of the model. In addition, the real-time correction of the prediction results further improves the prediction accuracy.

In the next experiment, we mainly observe the performance of various methods in different prediction periods. In this experiment, we fixed the number of training samples at 2,000, and the prediction period was divided into 1 hour, 6 hours, 12 hours, 18 hours, and 24 hours.

Table 4 and Table 5 provide the calculation results of various methods in RMSE and MAE under different forecast periods. Figure 6 shows the comparison results of the NSE of various methods in different prediction periods. From the above results, we can see that with the increase in the prediction period, the values of RMSE and MAE of all methods decrease; in contrast, the values of NSE increase. This indicates that the larger the prediction period, the lower the accuracy of flood forecasting, and

Table 2. RMSE performance of different training samples

Training Samples	500	1,000	1,500	2,000	2,500	3,000
Proposed	0.188	0.175	0.154	0.138	0.122	0.113
LSTM	0.196	0.189	0.168	0.152	0.144	0.125
CNN-LSTM	0.236	0.214	0.208	0.197	0.186	0.178
SVR	0.389	0.375	0.344	0.321	0.309	0.297

Table 3. MAE performance of different training samples

Training Samples	500	1,000	1,500	2,000	2,500	3,000
Proposed	0.102	0.094	0.088	0.079	0.071	0.062
LSTM	0.145	0.137	0.128	0.121	0.114	0.107
CNN-LSTM	0.164	0.152	0.144	0.136	0.128	0.121
SVR	0.304	0.297	0.288	0.269	0.261	0.250

Figure 5. NSE performance of different training samples

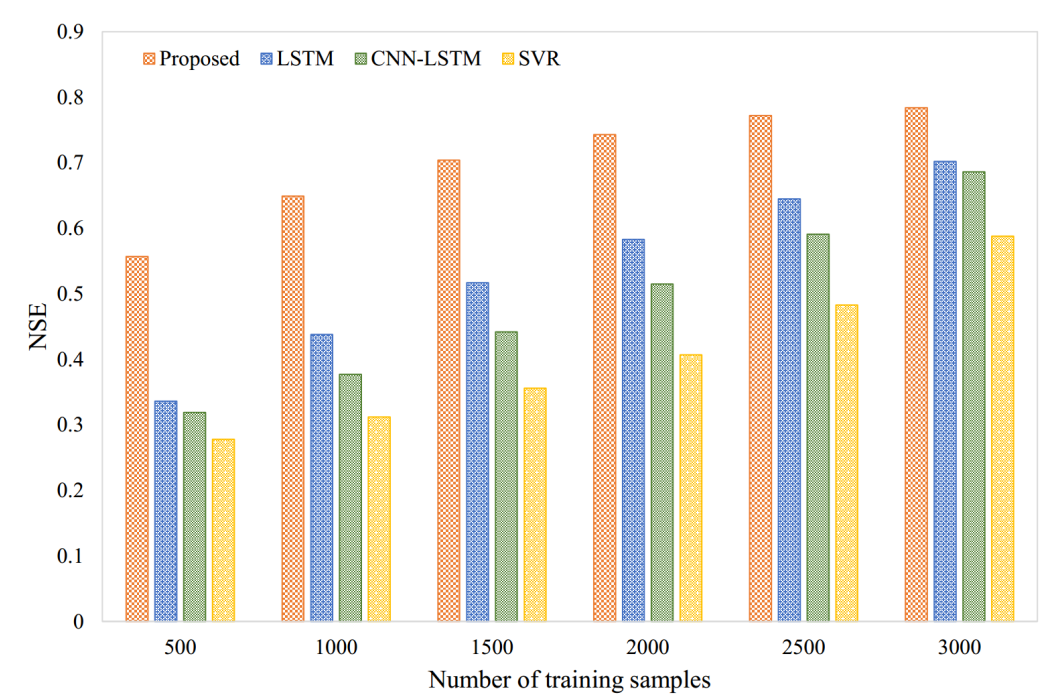


Table 4. RMSE performance of different prediction periods

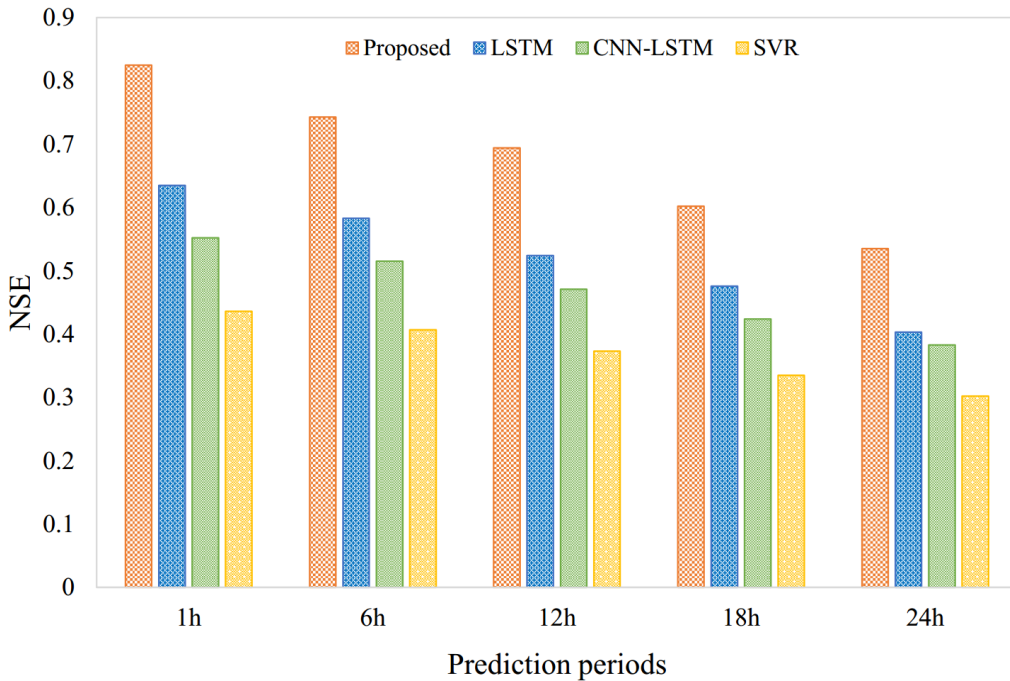
Prediction Periods	1 h	6 h	12 h	18 h	24 h
Proposed	0.125	0.138	0.176	0.235	0.292
LSTM	0.147	0.152	0.198	0.269	0.342
CNN-LSTM	0.209	0.236	0.273	0.306	0.353
SVR	0.303	0.321	0.356	0.388	0.413

Table 5. MAE performance of different prediction periods

Prediction Periods	1 h	6 h	12 h	18 h	24 h
Proposed	0.072	0.079	0.088	0.102	0.111
LSTM	0.103	0.120	0.131	0.139	0.147
CNN-LSTM	0.129	0.136	0.145	0.156	0.166
SVR	0.237	0.269	0.274	0.284	0.293

all flood-forecasting methods follow this rule. From the experimental results, SVR performed the worst, with all metrics significantly worse than those of the other three methods. The performance of LSTM and CNN-LSTM is also unsatisfactory, indicating that the size of the dataset has a significant impact on traditional prediction models, especially in larger prediction periods. Due to the transfer-learning strategy alleviating the dependence of long-term prediction on data continuity and diversity,

Figure 6. NSE performance of different prediction periods



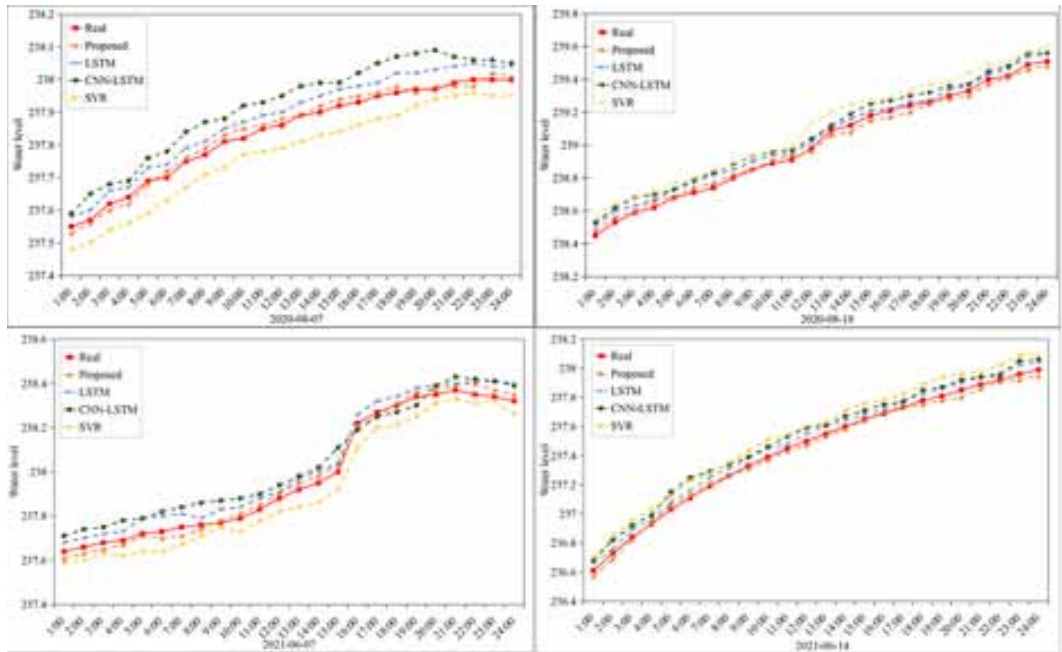
our proposed method outperforms other baseline methods in different prediction periods. The results show that the proposed method is not only effective for small sample datasets, but also very useful for large prediction cycles.

DISCUSSION

To show the advantages of the proposed method more intuitively, we forecast the 24-hour water level of Reservoir B on August 7, 2020, August 18, 2020, June 7, 2021, and June 14, 2021, and show the comparison results in Fig. 7. In the figure, the red solid line represents the measured water-level value, and the orange dotted line represents the prediction results of the proposed method. Obviously, the proposed method is more consistent with the measured results, which also shows that the prediction accuracy of the proposed method is the best. The experimental results also show that the combination of transfer learning and LSTM is better for improving the flood data training of reservoirs lacking data. As can be seen from Fig. 7, the forecast results of the proposed method are better than LSTM for almost the entire forecast period. Such comparison results show that the transfer strategy is very helpful for model training, and the historical data of similar reservoirs plays an active role in training the model. In addition, the feature extraction method and the error correction method proposed in this paper are also helpful to improve the prediction accuracy.

However, there are some aspects of the proposed algorithm that need further demonstration. For example, the experimental data used came from two reservoirs with similar geographical and climatic conditions. In this case, obtaining relatively ideal results seems to be in line with expectations. For the different-reservoir data, whether the ideal forecast results can be achieved needs further demonstration. The generalization ability of the model also needs further verification. Whether the data samples used for initial training of the model can cover most scenarios has a significant impact

Figure 7. Comparison of prediction results of time-series data



on the generalization ability of the model. Therefore, it is necessary to further test the generalization ability of the model and adopt appropriate methods to optimize the model.

CONCLUSION

To improve the accuracy of flood forecasting, especially for reservoirs with scarce historical data, this work proposes a deep-learning forecasting model incorporating transfer learning. In order to improve the accuracy and efficiency of prediction, this method uses the random-forest algorithm for feature extraction. On this basis, LSTM neural network is used to build a prediction model and a transfer-learning strategy is introduced into the model. For the problem of reservoir flood forecasting that lacks data, we first use historical data of similar reservoirs to train the prediction model, then use the data of the target reservoir to fine-tune the model parameters to obtain a flood-forecasting model suitable for the target reservoir, and finally use the error autoregressive algorithm to correct the forecast results and further improve the forecast accuracy. A series of Experiments shows that the proposed method is significantly superior to the classical method in terms of RSME, MAE, and NSE. The proposed method can provide a new means for flood forecasting in reservoirs lacking hydrological data. However, there are still some problems that need to be further studied, such as that the selection of similar reservoirs may have a great impact on the accuracy of the model and that other hydrological factors (such as elevation, geography, geomorphology, etc.) may also have a certain impact on the forecast results. In future work, we will focus on improving the generalization ability of the model and researching intelligent-correction algorithms.

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