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),