ENSO prediction based on Long Short-Term Memory (LSTM)

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Abstract. El Niño-Southern Oscillation (ENSO), as a global climate event with cyclical characteristics, often causes global climate anomalies and produces non-negligible economic and social impacts. Therefore, the prediction and research of ENSO events are important for understanding and solving global climate change issues. It has important scientific and practical significance. Previous research on ENSO events mainly used traditional statistical analysis and numerical simulation methods. This study explores the use of deep learning to improve the accuracy of El Niño-Southern Oscillation (ENSO) prediction. Based on long-term and short-term memory neural networks, the time series of meteorological and marine elements were analyzed. In the meantime, the sea surface temperatures (SST) and sea level pressure were predicted to calculate the Southern Oscillation Index (SOI) to reflect the ENSO phenomenon. Finally, this article takes the Niño3.4 regional data from the National Centers for Environmental Prediction (NCEP) dataset as an example, and uses the model proposed in this paper to compare with traditional statistical regression methods. The results show that the Long Short-Term Memory (LSTM) has a good effect in the prediction of ENSO events, and has certain scientific significance and practical value for the prediction of ENSO events.

1. Introduction

El Niño-Southern Oscillation (ENSO) is a global climate event. It has periodic characteristics and has a significant impact on global climate change [1]. The ENSO events is one of the most important factors affecting climate disasters such as summer droughts, floods, and low temperatures in the winter. It is also the strongest interannual change signal in the tropical Pacific air-sea coupling system [2]. At the same time, severe ENSO events often lead to global climate anomalies and have economic and social impacts that cannot be ignored. Therefore, prediction and research of ENSO events are also of great scientific and practical significance for understanding and solving global climate change problems [3]. The current research on ENSO events is mainly to analyse and study the causes and future development trends of ENSO events by defining indexes. However, due to the different physical mechanisms of different types of ENSO events, there is currently no unified index standard for the diagnosis and prediction of ENSO events. With the rapid development of artificial intelligence, machine learning methods can be used to select key indexes and make ENSO events predictions. In addition, related scholars use numerical models to simulate and study ENSO events, but long-term
model integration will cause a huge accumulation of errors and eventually lead to the failure of prediction.

Due to the nonlinear interaction of the air-sea system and its own chaotic characteristics, in practice, most numerical prediction models are difficult to simulate the annual average changes of elements such as SST and cannot accurately predict the occurrence and development of ENSO events. In addition, due to the randomness of the spatiotemporal evolution of different types of ENSO events, traditional statistical regression analysis methods also have great uncertainty in predicting ENSO. In recent years, with the continuous development of machine learning methods, many scholars have started to use machine learning or deep learning technology to forecast meteorological elements and short-term climate predictions, and have obtained relatively satisfactory results [4,5]. If the SST or index prediction problem is defined as a time series regression problem, a long-term short-term memory neural network (LSTM) can be used to predict the ENSO events.

2. LSTM-based ENSO events prediction model

2.1. Problem definition

El Niño and Southern Oscillation events occurred in the eastern Pacific region, which can be divided into uniform grids by using longitude and latitude information. Each grid point has multiple meteorological element information, including sea surface temperature (SST), sea surface wind field, and sea level pressure. At a specific time, these meteorological element information is stored in a two-dimensional matrix in a horizontal distribution. If the change information of meteorological elements is taken as a research object within a period of time, the information of these meteorological elements is stored as three-dimensional matrix data and processed.

In this study, the problem of forecasting ENSO events is considered as a regression forecasting problem. A neural network model is used to solve such a statistical problem. To predict the changes in meteorological elements such as sea temperature (SST) and sea level pressure based on historical meteorological information. Further, calculate the Southern Oscillation Index (SOI), the Oceanic Niño Index (ONI), etc. For example, according to the sea surface temperature information of M months and other relevant meteorological element information, the sea temperature changes from M + 1 to M + t months are predicted, where t represents the forecast duration.

2.2. RNN model and LSTM introduction

Recurrent neural network (RNN) is developed from a feedforward neural network (FNN). There is a certain difference between them. FNN only use layers and connections between layers to achieve information transfer. The loop structure was introduced in the network, that is, the connection between the neuron and itself was established [6]. Through this connection, the RNN can store the input at the previous time point in the network and affect the network output in the next step. In contrast, FNN can only map the input to the output layer through the hidden layer, and RNN can map a complete piece of historical information to each output neuron, making full use of historical information. Therefore, compared with FNN, RNN has more advantages in the prediction problem where the input and output are time series data.

Long Short-Term Memory (LSTM) is a special form of RNN. It introduces the concept of gate and adds the function of long-term and short-term memory so that the information is no longer attenuated. It is solved by designing forget gate, input gate and output gate. It has solved the long-term dependence problem of RNN, and has excellent performance in language translation, machine control, document summary, and speech recognition [7]. For the long-term series of meteorological data, consider that the El Niño and Southern Oscillation events are the products of the interaction between the ocean and the atmosphere. From the perspective of the physical mechanism, SST, sea surface wind field, sea level pressure, and sea surface height are all related to ENSO events. So long-term short-term memory (LSTM) is considered for predictive research on multifactor-related ENSO events.
2.3. Experimental methods and steps

According to the characteristics of the ENSO events, LSTM is used to predict the ENSO events using the historical information of time series such as sea level pressure, sea surface temperature, and sea surface wind field. The data used in this research is the reanalysis data of the Climate Forecasting System of the National Centers for Environmental Prediction (NCEP). The data set includes sea temperature, sea surface wind speed, sea level pressure, and precipitation rate, etc. Data set time span from 1979 to 2018.

The training set and test set are obtained by sliding method. First, set the sliding window size to the sequence length, then use the moving average method to expand the selected data set, and finally slide the amplified data set through the sliding window. The samples required for model training are divided into a training set and a test set according to a 4:1 ratio. In addition, this paper uses Root Mean Square Error (RMSE) as the loss function during training. The data set is processed, and the Southern Oscillation Index (SOI), Nino3, ONI Index, PNA Index, and average precipitation are calculated. Finally, a correlation analysis is performed on the obtained results to determine the variables input to the prediction model, thereby predicting the occurrence of ENSO events.

3. Analysis of results

This study uses the sea surface temperature (SST), sea surface wind field, sea surface pressure, geopotential height data and precipitation data to calculate SOI, Nino3, ONI, PNA, and average precipitation, etc. Calculate the correlation between them to determine the dependent variable of the input. The indexes and statistical results are shown in Figure 1. According to the results in the figure, it can be seen that each index has the characteristics of periodic changes, so it is feasible to predict the ENSO event through a deep learning model.

![Figure 1 Inter-annual changes of different indices](image)

The correlation degree of each index and statistical results is shown in Figure 2. According to the results in the figure, it can be concluded that the correlation between SOI and ONI, Nino3 and precipitation is the largest. Therefore, by entering relevant data into the deep learning model, SOI is calculated. The SOI is used as a prediction index to analyze and predict the occurrence of ENSO events.
In order to test the reliability of the prediction results of the deep learning model, the Southern Oscillation Index (SOI) prediction results were compared with the statistical results of actual observation data. The comparison results are shown in Figure 3. The solid blue line is the observation result, and the solid red line is the prediction results based on LSTM. By comparison, it can be concluded that the prediction results based on the LSTM are basically consistent with the observations. Therefore, the prediction of ENSO events based on the LSTM has some scientific significance and applicable value.

4. Conclusion
This paper studies the prediction of ENSO events based on LSTM. By preprocessing and diagnosing meteorological time-series data, we select the variable with strong correlation with ENSO events to train a prediction model, and use the prediction results to calculate Southern Oscillation Index (SOI) which reflects the ENSO phenomenon and has achieved good results. The results of this study show that deep learning methods have great potential in the field of ENSO events prediction. It was also
found in the experiment that the construction of the prediction model depends heavily on the quality of the data set. When there is a large error in the input data, the prediction result is poor. In the future, a regularization method will be introduced to further study the problem.

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