Prediction of ENSO Based on NCEP Reanalysis Datasets

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Abstract. In recent years, ENSO has been a climate phenomenon that has profound effects on global climate patterns and extreme events. Nino3.4 is a data representation of ENSO. In this study, CNN and LSTM were used to fit and foresee the data in the NCEP reanalysis data set. The findings demonstrate that while the LSTM model can also accurately forecast the changing tendency, it is relatively the effect of CNN is poor, and there is a situation where the simulation value is generally small, CNN does a good job of forecasting the Nino3.4 index, which reflects ENSO. When the index fluctuates significantly, the selection, however, has a tendency to be conservative. Additionally, this study's sample size was quite high, which led to more precise prediction results than in earlier research. To help the ENSO forecasting model forecast more precisely and timely, this study offers various references for its improvement of further study.

Keywords: ENSO; prediction; NCEP.

1. Introduction

The strong climate phenomenon known as El Niño -Southern Oscillation (ENSO) has an enormous effect on the planet's climate. The interaction of the atmosphere and the ocean causes it to happen in the tropical Pacific. This is facilitated through feedback between surface wind and sea surface temperature (SST). People's perceptions of El Niño, which was first recognized in 1893 as a warmer area of ocean circulation that influences the climate off the coast of Peru, have changed throughout the previous century. The identification of ENSO as a basin-scale occurrence occurred in the 1960s as a result of coupled relationships between the ocean and the atmosphere [1]. As a result of an important international research drive in the 1980s and 1990s, it became substantially easier to track, evaluate, and foresee ENSO and its global effects [2]. The understanding of ENSO has developed over the past 20 years as new layers of complexity in ENSO dynamics and prediction have been found.

Some researchers have started to experiment with using machine learning to enhance ENSO prediction abilities as a result of the recent explosive growth of large amounts of data and machine learning techniques. Ham et al. based on reanalysis and global SST and ocean heat content data in the model data, trained the model through the convolutional neural network method, obtained a higher ENSO prediction skill than the current mainstream climate model, and the Nino3.4 indicator outperformed the 12-month prediction's correlation coefficient, which was greater than 0.65 [3]. Petersik and Dijkstra also achieved a comparable level of prediction ability by using the neural network method to simulate the ENSO index and the level of ocean heat with little to no input [4]. The latest work combines the empirical model Decomposition and time convolutional network method to further increase the correlation coefficient of Nino3.4 12 months in advance to 0.83.

The ENSO phenomenon has a significant impact on worldwide temperature and precipitation. It is associated with various interannual climate variations that affect the planet, including severe weather events such as floods, hurricanes, droughts, and cyclones. These events can cause disasters for humans, birds, and other creatures. Enhancing our knowledge of the mechanisms that govern ENSO's magnitude, execution, duration, certainty, and worldwide effect is essential, given its societal and environmental significance.

This paper aims to predict ENSO by using the NCEP reanalysis dataset. It will compare and analyze existing ENSO prediction models, and then evaluate their accuracy by comparing them with the actual situation. The paper will also propose suggestions for improving the current prediction model and future relevant model research. In the next part of this article, one will introduce the data sources for preparing visualizations and the basic methods for numerical simulation with models. Section 3 introduces the simulation results of previous models, compares them with the simulation results of NCEP data, and explains and discusses the final results. The limitations of this study are examined in Section 4 along with potential future research areas. Section 5 provides an overview and summary of the full-text outcomes.

2. Data and Method

Nino3.4 SST was published by the National Centers for Environmental Prediction (NCEP) of the National Oceanic and Atmospheric Administration (NOAA), and it covers a large period and a lot of data. However, because the prediction model must be trained on a large number of samples, this study simulates the prediction model using the data to get superior prediction outcomes. Nino3.4, which measures the average sea temperature anomaly in Nino3.4 region (170°W-120°W, 5°S-5°N), is a crucial tool for tracking the ENSO phenomena. Nino3.4, a continuous value, indicates an ENSO event when five consecutive months of A monthly temperatures exceed 0.5°C. The HadISST1 dataset was used to generate the data for this study from PSL [5]. The time range, which runs from January 1870 through April 2023, is monthly. The data has a temporal resolution of one month. On the website of NCEP (https://psl.noaa.gov/gcos_wgsp/Timeseries/Nino34/), one can download the Nino3.4 index.

Nino3.4 is presented as a period series. Based on this time series data, we can speculate on the future short-term changes in the Nino index. After exploratory data analysis (EDA) and feature engineering (FE), In this research, Nino3.4 will be predicted using Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models, and the predictions will be compared to the actual data. It will be possible to improve ENSO forecasting over time by contrasting the outcomes of the two models' predictions. A subset of feedforward neural networks that incorporate convolutional computing is known as CNN [5]. It is one of the deep learning algorithms that best exemplifies the field. A convolutional layer and a pooling layer make up a feature harvester in convolutional neural networks. The convolutional layer decreases the quantity and complexity of the variables in the network by connecting a neuron to only some of its adjacent neurons. A modified form of the ordinary Recurrent Neural Networks (RNN), LSTM is sometimes referred to as a long-short-term memory structure [6]. It successfully captures the conceptual connection between lengthy sequences and mitigates the gradient absence or explosion issue when compared to standard RNN [7]. While also being more intricate, the LSTM structure can be broken down into four distinct components for analysis. The structure is displayed as shown in Fig. 1

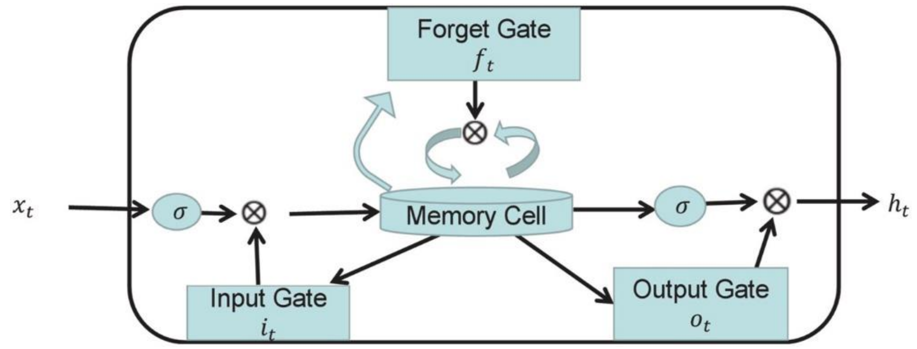

Fig. 1 The schematic of Long Short-Term Memory.

3. Results and Discussion

3.1. Simulations Results

Certain scholars employ transferred learning to develop a convolutional neural network (CNN) initially on the past models and then on revision from 1871 to 1973 to get over the lack of observation material [3,8]. They discover that the ENSO amplitude is accurately foretold by CNN, as seen by

Nino3.4 for the December-January-February (DJF) period for the 18-month-lead estimate (as illustrated in Fig. 2.

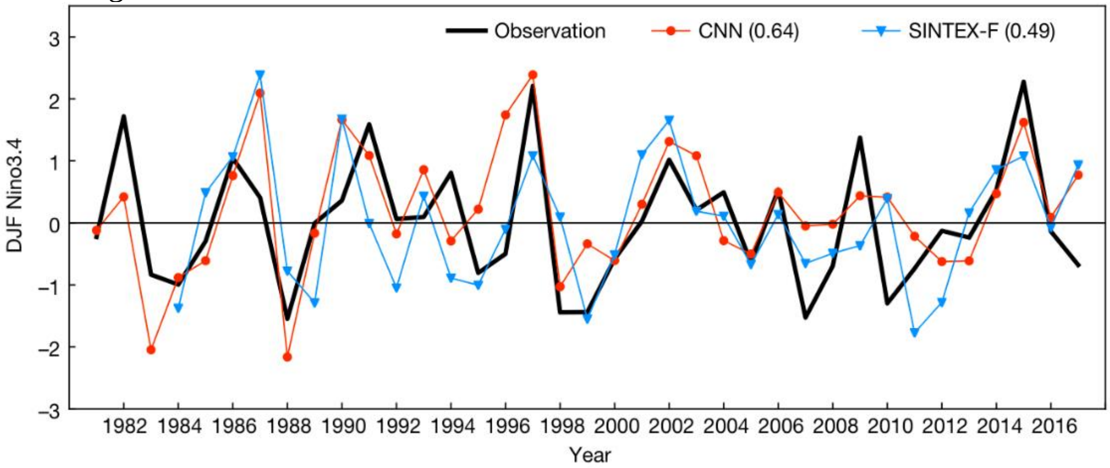

Fig. 2 ENSO predictions from the CNN model.

The research discovers that, over the verification period from 1984 to 2017, the CNN model's Nino3.4 had a substantially greater all-season association ability than the most sophisticated dynamic forecasting system available at the time. Therefore, CNN models are powerful tools for predicting ENSO events and analyzing their related complex mechanisms. Some researchers used the LSTM model to predict the ENSO of SON 2014 MJJ 2015 [9, 10]. The red line, which runs from the JAS 2013 through OND 2014 seasons, represents the real amount of ENSO (i.e., Nino3.4 SST anomaly). The LSTM neural network may be able to learn the long-term temporal dependence of the ENSO phenomena and model its non-linear properties, such as between 6 months, 9 months, and 12 months, based on the outcomes that the LSTM model predicted. It is irrelevant where the performance gap lies (given in Fig. 3). As a result, an LSTM using network measurements has an equal chance of correctly predicting ENSO phenomena in longer multiple steps as it does in shorter multiple steps. The tendency towards the goal, however, is considerably different, which may be explained by the small total number of informational points (804).

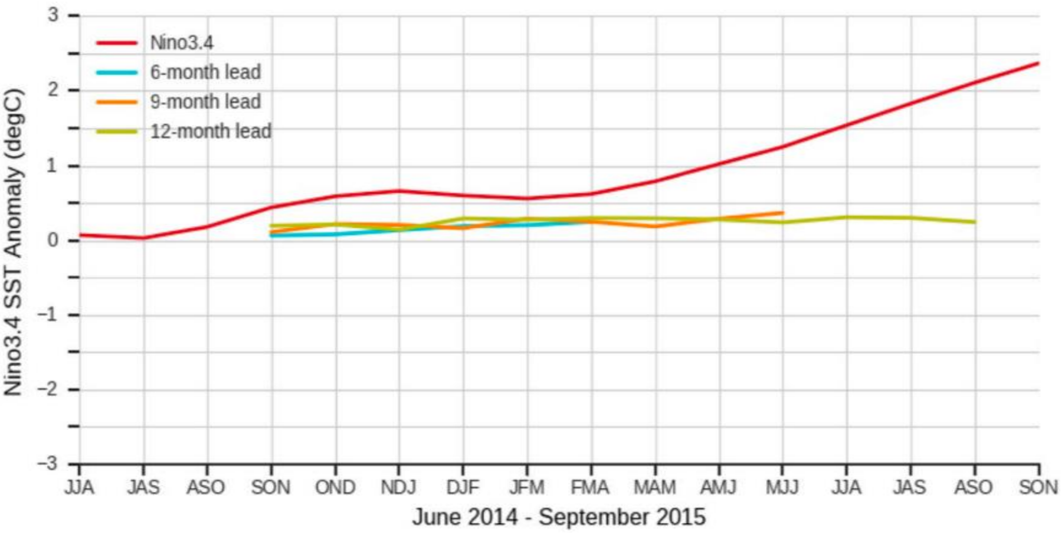

Fig. 3 ENSO simulation made by LSTM from SON 2014 to MJJ 2015.

3.2. Observations

This study first uses a one-dimensional convolutional neural network to predict Nino3.4. In this research, CNN is trained using a sizable amount of downloaded Nino3.4 monthly average data so that the model can absorb and reproduce the original data. As seen in Fig. 4, CNN performs a highly accurate estimate of Nino3.4 with a respectable magnitude. It has been observed that the CNN model has a good fitting effect in the range of small amplitudes, but it tends to be conservative for the fitting of large changes. This is because CNN focuses on local features, and the prediction of future data tends to converge or oscillate. To better compare with previous research results, this study uses CNN to predict and map the average Nino3.4 in the winter from 1979 to 2021, that is, in the December–January–February season (presented in Fig. 5). The study found that the simulated trends of the two research models are consistent, and they both reflect typical situations such as the ENSO in 1982. The forecast of Nino3.4 is also more accurate, and the simulation value agrees with the actual observation value since the amount of data used in this research is significantly greater than that of previous ones. In particular, this study is more accurate in fitting extreme El Niño years, while previous models have certain deviations and cannot fully reflect extreme conditions.

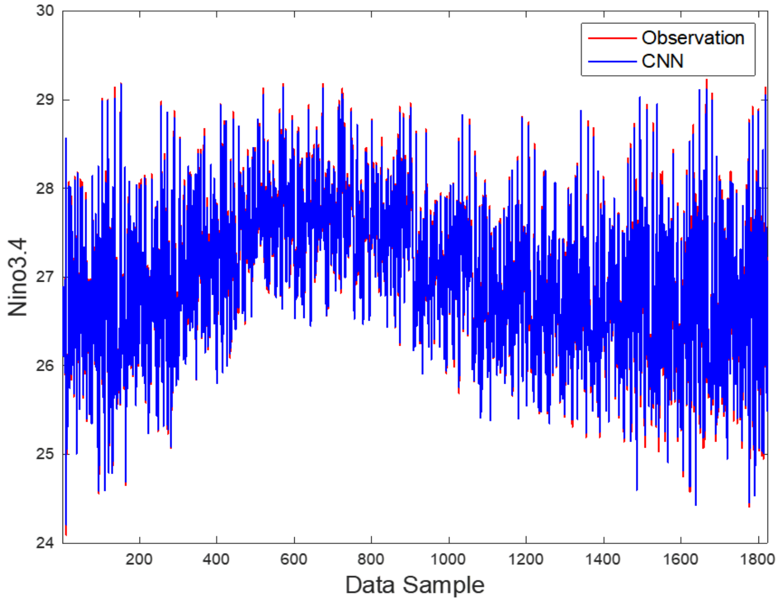

Fig. 4 ENSO forecasts of the CNN model.

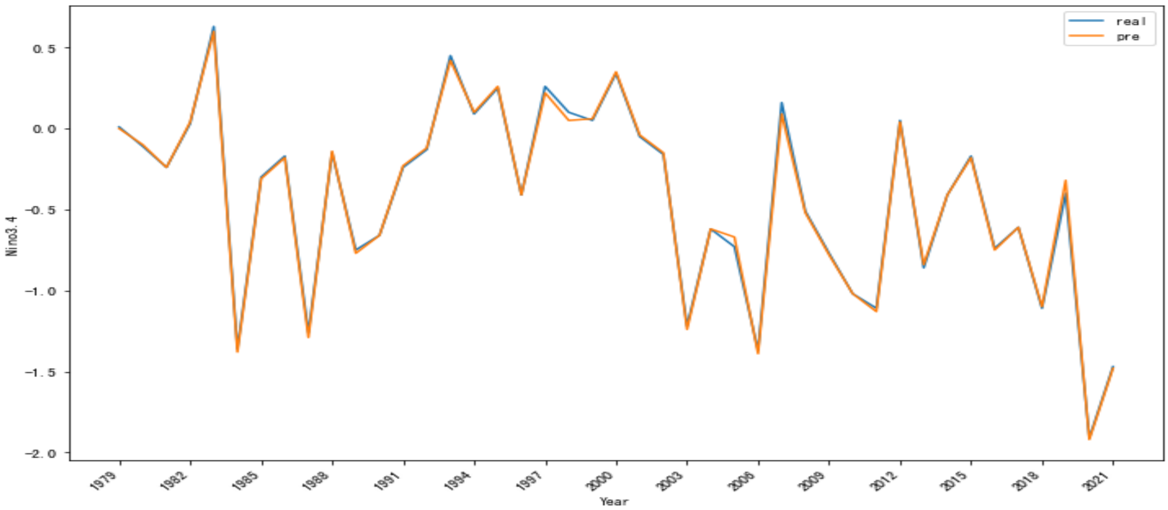

Fig. 5 Winter Nino3.4 index period series for ENSO prediction using the CNN model.

To solve the problem that the model cannot learn experience from past information, this study introduces LSTM, as shown in Fig. 6, hoping that the experience model can provide decision-making for our predictions. The root MSE of LSTM is larger, and its fitting impact is not as good as that of the original CNN, despite the reality that the entire fitting consequence of the model is greater than that of CNN, as can be discovered from the prediction results based on LSTM. It is too small and generally does not fit well with the larger Nino3.4.

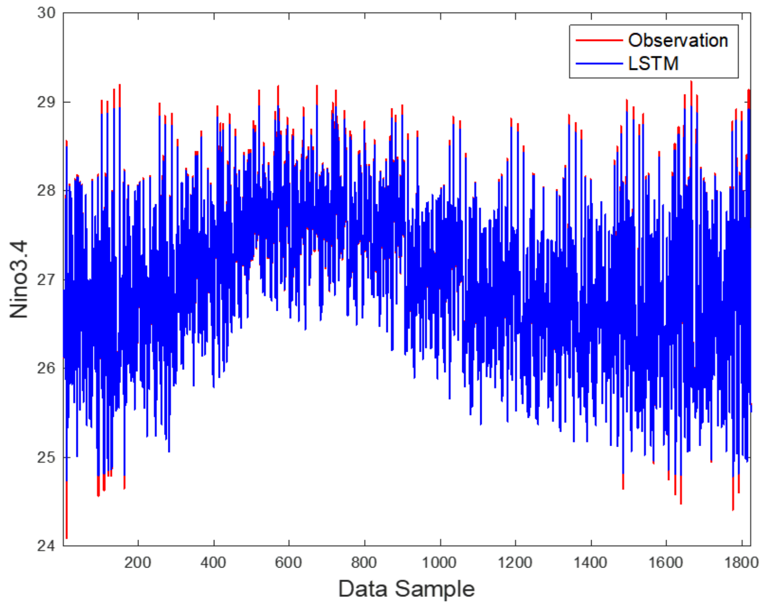

Fig. 6 ENSO forecasts of the LSTM model.

3.3. Explanation

CNN estimates Nino3.4 more precisely than LSTM, according to a comparison of the two models, and can more clearly fit the extreme ENSO event. Although LSTM also has a relatively good fitting effect, the overall predicted value of Nino3.4 is smaller than the actual value, and there are obvious errors. In addition, in running LSTM, due to the large time-series span, the model has the problems of large calculation and is time-consuming. Overall, this study's findings demonstrate that CNN works superior to LSTM at predicting the ENSO phenomenon using Nino3.4, and the prediction of extreme ENSO is very accurate. This accomplishment offers a technique for matching Nino3.4 to the CNN and LSTM models and also serves as a useful benchmark for enhancing the simulation model going forward to more accurately forecast ENSO episodes.

4. Limitations and Prospects

Although CNN utilized in this study outperformed LSTM in terms of its ability to forecast Nino3.4, it can more precisely depict Nino3.4's changing trend. However, CNN and LSTM are both just getting started, and there are some problems. For example, although CNN has a good performance on the original data set, the effect is not so good in the prediction of future data. This is because CNN pays attention to local features, and in the speculation of future data, the data will tend to converge or oscillate. Although LSTM can preserve long-term information, the MSE of this model is relatively high, and the fitting effect is not as good as that of the original CNN. Both forecasting models have great advantages and obvious shortcomings, which need to be further developed and perfected.

In the future, the following two possible solutions will be considered to further reduce the prediction error. On the one hand, by introducing advanced empirical post-processing technology to correct the forecast results of the model and compare the correction effects of the two models; on the other hand, because CNN focuses on local information, LSTM is good at preserving long-term information, and can fully utilize the two models by combining the two models. Their respective advantages form a CNN+LSTM model. At the same time, based on the idea of "super ensemble forecasting" [11], according to the historical performance of each model, a linear or nonlinear method is used to assign optimal weights to the model ensemble. ENSO multi-model ensemble prediction started relatively late in my country, and in the future, it will continue to increase investment and carry out in-depth research. It is hoped that through unremitting efforts, the forecast model can release ENSO forecast results in a timely and accurate manner, providing reliable support for operational forecasting and disaster prevention and mitigation.

5. Conclusion

To sum up, this study compares and analyzes the prediction effect of CNN and LSTM models on Nino3.4 based on the predecessors. The results show that CNN can predict Nino3.4, but the fitting tends to be conservative when the index changes greatly; although LSTM can also fit the changing trend well, it is relatively the effect of CNN is poor and is a situation where the simulation value is generally small. In addition, the amount of sample data in this study is large, so compared with previous studies, more accurate prediction results have been obtained. Even so, there are still some problems in this study, such as the predicted values of the two models being conservative, which need to be further developed and improved. In the future, it will be considered to forecast ENSO events more accurately by introducing empirical post-processing technology to modify the model and combine the two models. ENSO is closely related to the global climate and has a great impact on the development of human society. This paper provides some references for improving the ENSO forecasting model, helping the model to forecast more quickly and more accurately.

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