Research on the Application of Radar Echo Model Based on LSTM in Immediate Weather Forecast

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Abstract. This research analyzed the issue of radar echo extrapolation based on the Long Short-Term Memory (LSTM), established the echo extrapolation algorithm on the basis of the LSTM model, and explored the practical application of this algorithm in the prediction of rainfall volume and in the comprehensive similarity of cloud images. The practiced extrapolation test showed that the average comprehensive similarity of the radar echo extrapolation algorithm based on the LSTM model in the extrapolation within 15 minutes and 20 minutes was 87% and 80% respectively, and the similarity exceeded 70% in the extrapolation test in a relatively longer term. In the rainfall prediction of the next 20 frames of images, this algorithm got an instant hit rate of 64.1%, a false rate of 20.6%, and a key success index of 43.8%. Compared with the traditional radar echo extrapolation algorithm, this echo extrapolation algorithm based on the LSTM model had an excellent application effect in the aspect of weather forecast. The contents of this research can provide scientific and effective reference materials for the subsequent application researches of the technology in weather forecast.

1. Introduction
In recent years, immediate weather forecast has become a key issue in the research of meteorology [1]. Immediate weather prediction refers to the prediction of high temporal and spatial resolution for rapidly changing weather phenomena in a short time [2]. When encountering thunderstorms, severe convection, heavy rainfalls, sandstorms and other rapidly evolving and severely destructive weather phenomena, the particular significance of immediate weather forecasting will be self-evident, for accurate weather forecasting can provide strong supports for the scientific protection performed in society [3]. The radar echo extrapolation technology is the main technical means for this immediate weather prediction [4]. This technology mainly refers to determining the intensity distribution of echo and the moving speed and direction of storm cells, precipitation areas and other factors according to the echo data detected by weather radar, and predicting the radar echo state after a certain period of time through the linear or nonlinear extrapolation of echo body [5]. Improving the accuracy and efficiency of radar echo is also one of the focuses of the researcher.

At present, with the rapid development of the internet, the machine learning and the artificial intelligence technology, the related concepts of neural network have gradually affected the development of all walks of life [6]. Among them, the RNN (Recurrent Neural Network) deep network model is widely used in handwriting recognition, speech recognition, natural language processing and many other fields because of its excellent performance in dealing with and predicting the timing problem [7]. While in the study of RNN, LSTM algorithm is further optimized and researched on the basis of RNN, which
is considered as a promising neural network model [8]. In meteorological researches, the research based on neural network has become a research focus. Based on the related application and theoretical technology of LSTM, this study designs the radar echo prediction model based on LSTM, and explores as well as analyzes the specific application of this model in the analysis of the comprehensive similarity of cloud images and the results of prediction for rainfall volumes. In consideration of its concrete prediction results, in order to further clarify the application effect of the model, this research compares and analyzes the prediction effects of this model with other models, and further reflects the application effects of this method. The purpose of this research is to provide a reasonable reference for the related researches of immediate weather forecast.

2. Methods

2.1 Structure of the Long Short-Term Memory
RNN is a commonly used neural network algorithm at this stage, which can handle data of different lengths and different sequence types [9]. In practical applications, it is found that RNN can only be used in a small range whereas it cannot handle the data of long sequences well, which will lead to the output of long sequences while forgetting the input of a relatively longer distance [10]. For this reason, LSTM arises at the historic moment. Neural network can be expanded in LSTM based on time, which is suitable for the processing and prediction of the problem of relatively longer interval in time series [11]. LSTM neural network improves the shortcomings of the traditional neural network. It can remember the important knowledge learned, and meanwhile forget the unimportant knowledge, so as to avoid information redundancy. LSTM neural network mainly adds a control layer in the hidden layer of RNN as the module of long-term and short-term memory. Assuming that the traditional hidden layer has only one state or one level, it can work according to the short-term memory [12]. In contrast, the LSTM neural network adds a control layer to preserve the long-term state [13]. The schematic diagram of LSTM neural network based on time is shown in Figure 1.

![Figure 1 The Schematic Diagram Based on Time](image)

It can be seen from Figure 1 that at time t, the inputs of the neural network include the output values of the hidden layer (h layer) and the control layer (c layer) at the previous time and the input value of this sequence at time t; the outputs of neural network include the output value of layer h at time t and the output of layer c at time t. The control layer of LSTM is mainly controlled by three gates: the input gate that judges whether the long-term state should be saved, the forgetting gate that judges whether the input value should be output to the long-term state, and the output gate that judges whether the long-term state value should be used to adjust the output [14]. The structure of these increased gates is also the most important difference between LSTM and RNN.

2.2 A Design of the Radar Echo Model Based on LSTM
The LSTM radar echo model involved in this research is carried out in the open source TensorFlow deep learning framework, and the TensorFlow deep learning framework is used as the research and practice platform of deep neural network. Not only is it flexible in use and convenient in application, but it also supports the cross-platform and cross-device application effect, at the same time of supporting the
calculation acceleration of CPU with a use in practical applications [15]. TensorFlow uses data flow in calculation and makes expression by constructing a directed graph. The data flow between nodes is called the tensor, and the arrow indicates the flow direction of nodes [16]. The calculation process is as follows in Figure 2:

![Figure 2 Concrete Process of TensorFlow Calculation](image-url)

The LSTM radar echo model involved in this research is designed and studied on the basis of LSTM. It can be seen from the above studies that the memory unit of LSTM has three gate structures, increasing the computational complexity of LSTM, and thus increasing the amount of calculation to a great extent, which is not conducive to practical application [17]. Therefore, this research will firstly try to reduce the computational complexity by reducing the gate structures to improve the training speed. The model involved in this research actually omits the output gate of the LSTM model and removes the calculation process of the output gate. The final variables can then be attained as follows:

$$b_i' = h(s_i')$$  \hspace{1cm} (1)

Meanwhile, in terms of calculating the learning rate, the network model involved in this research is to adjust and optimize the learning rate by using a combination of the fixed learning rate strategy and the exponential strategy [18]. At the beginning of the training, the research will use a relatively larger learning rate at a speed of the speed-up training. However, in the subsequent operation, the learning rate will be lowered down in turn to improve the convergence stability. The involved speculate formula of learning rate is as follows:

$$LR_i = \text{init-}LR \ (i \leq m)$$  \hspace{1cm} (2)

$$LR_i = \text{init-}LR \times \text{decay}^{(i-m)} \ (i > m)$$  \hspace{1cm} (3)

Through the above formulas, it can be seen that when using this learning strategy, the learning rate will gradually decrease, and the final learning rate will gradually tend to be 0, but the value of each decrease can be relatively smaller. The advantage of this feature is that manual adjustment can be avoided, and the performance can be guaranteed with relatively higher degree of convergence and stability.

The activation function used in this research is ReLU (Rectified Linear Unit) function [19]. The formula and image of this activation function is as follows:

$$f(x) = \max(0,x)$$  \hspace{1cm} (4)
Figure 3 Image of ReLU Function

It can be seen from Figure 3 that the ReLU function is applied to perform unilateral suppression, which reduces the interdependence of parameters and alleviates the overfitting problem. Meanwhile, since the derivative of the ReLU function on the non-suppressed side is 1, the gradient can be prevented from disappearing [20]. In addition, the derivation of the ReLU function shows that using this function for network training has relatively smaller computational complexity, which is conducive to practical application [21].

The specific operation process of the model involved in this research is as follows. Firstly, the input data need to be vectorized, so as to transform the data into One-hot encoding form [22]. To prevent the data from overfitting, the input retention ratio shall be controlled. When the model is trained, after the predicted output value is obtained, the cross-entropy function shall be used to calculate the cross entropy of the predicted output and the real image, and it shall be used as the training loss to correct the network parameters with the random gradient descent method. When the model is tested, after the predicted output value is obtained, the system will perform SoftMax regression to obtain the probability of each pixel in accordance with each label respectively. When running the verification process and the test process, the predicted reflectivity factor diagram shall be saved in binary files in real time, so as to evaluate and adjust the model in the future.

2.3 Source and Processing of the Experimental Data
The data used in this research come from the echo data of October 2020 in a certain part of central China. The actual research object is the reflectivity factor diagram of the rainfall weather process. The echo data of a rainfall weather are selected, and the reflectivity data of the second elevation angle are selected as the experimental data. Since the echo data are saved in the mode of polar coordinates, it is necessary to convert them into rectangular coordinate system for subsequent operations. The extrapolation range of this research is 240 km, the distance between the two pixels is 1 km, and the image center is taken as the circular point. The specific conversion formula is as follows:

$$\rho^2 = x^2 + y^2, \quad \tan \theta = \frac{y}{x} (x \neq 0)$$

(5)

2.4 Experimental Environment and Evaluation Method
The experimental environment of this research is as follows:

| Type          | Parameter          |
|---------------|--------------------|
| Operating environment | Windows 10        |
| CPU           | Inter Core i7 8th Gen |
| RAM           | 64G                |
It can be seen from the above Table 1 that in this research, the operating system is Windows 10 software, the Python software is mainly used as the development language, and the data need to be preprocessed with the Eclipse development environment before entering the network.

The main evaluation index of this study is the comprehensive similarity of cloud areas. The comprehensive similarity is mainly obtained by putting the similarity of each region into weighting calculation. This research mainly sets the similarity weight of the core region as 0.4, the similarity weight of the non-core region as 0.2, the similarity weight of the high-intensity region as 0.3, and the similarity weight of the low-intensity region as 0.1. The specific calculation formula is as follows. Firstly, the real cloud image at time is set as $M(t)$, the core area as $S_1(t)$, and the non-core region as $S_2(t)$. At the same time, the intensity of the reflectivity at a certain point is set as $R(p)$, and the number of points (which conforms to $R(p) \geq I$) in both the real image and the extrapolated image is set as $n_i$, while the number of points in only one of those images is set as $n_i'$.

The similarity of the core region is:

$$p_1 = \frac{\min \{ S_1(t), S_2(t) \}}{\max \{ S_1(t), S_2(t) \}}$$ (6)

The similarity of the non-core region is:

$$p_2 = \frac{1}{n} \sum_{i=1}^{n} \frac{\min \{ S_1, S_2 \}}{\max \{ S_1, S_2 \}}$$ (7)

The similarity of the high-intensity region is:

$$p_3 = \frac{1}{n} \sum_{i=1}^{n} \frac{\min \{ S_1, S_2 \}}{\max \{ S_1, S_2 \}}$$ (8)

The similarity of the low-intensity region is:

$$p_4 = \sum_{i=5,10,15} \frac{n_i}{n_i + n_i'}$$ (9)

According to the above settings, the calculation formula of the comprehensive similarity is:

$$p = \sum_{i=1}^{5} w_i p_i \quad w_i = \{0.4, 0.3, 0.2, 0.1\}$$ (10)

Meanwhile, this research also calculates the conversion formula of radar echo intensity (db) and rainfall volume (mm/h):

$$Z = 10 \log a + 10 \log R$$ (11)

In this formula, $Z$ is the intensity of the radar echo.

The rainfall volume of each grid point can be calculated according to formula 11. Meanwhile, the research mainly introduces POD (the probability of detection), FAR (false alarm rate) and CSI (critical success index) to evaluate the prediction results [23]. The main calculation formulas of these indexes are as follows:

$$POD = \frac{n_{success}}{n_{success} + n_{missed \, alarm}} \times 100\%$$ (12)
In these formulas, $n_{\text{success}}$, $n_{\text{missed alarm}}$, $n_{\text{false alarm}}$ represent the number of the grid point of success, missed alarm and false alarm, respectively.

### 3. Results and Discussion

#### 3.1 Evaluation Results of the Comprehensive Similarity of Cloud Images

In this research, the comprehensive similarity is calculated with the radar echo model based on LSTM under different extrapolation times, and the specific results are shown in Figure 4.

![Figure 4 Comprehensive Similarity of Extrapolation Prediction](image)

Figure 4 shows that when the radar echo model based on LSTM is used for extrapolation prediction, the comprehensive similarity of extrapolation prediction at the 15th minute is 87%, and that at the 20th minute is 80%. With the gradual extension of the extrapolation time, the prediction time at the 25th minute and the 30th minute is 76% and 72%, respectively.

#### 3.2 Evaluation Results of the Rainfall Volume

Primarily, the changes of each parameter of rainfall volume were analyzed in the prediction of the next 20 frames. The specific contents are as follows in Figure 5.

![Figure 5 Prediction of the Research Model in the Next 20 Frames of Images](image)

It can be seen from Figure 5 that when using this algorithm, POD is 64.1%, FAR is 20.6%, and CSI is 43.8%. In general, this algorithm performs well in the overall hit rate, especially in the FAR index.
Meanwhile, the changes of POD, FAR and CSI calculated by the radar echo model based on LSTM in different time ranges were analyzed in this research, and the specific results are as shown in Figure 6.

![Figure 6 Prediction Results of the Research Model Varying with Time](image)

It can be seen from Figure 6 that the LSTM radar echo model shows that with the passing of time, the value of FAR gradually increases, and the values of POD and CSI gradually decrease.

3.3 Analysis of the Algorithm Results in Comparison

In order to further clarify the superiority of the model used in this research, the algorithm involved in this research is compared with other algorithms. Firstly, in terms of the comprehensive similarity of cloud images, the method used in this research is compared with the edge corrosion expansion method [24]. The results are as follows in Figure 7.

![Figure 7 Comparison Results of Comprehensive Similarity of Cloud Images](image)

It can be seen from Figure 7 that the comprehensive prediction results of LSTM radar echo model at the 5th min and the 10th min are better than those of edge corrosion expansion method. In summary, the method used in this research has certain advantages and accuracy, with an excellent application effect.
In the prediction results of rainfall volume, this research compares the LSTM radar echo model with the traditional optical flow method to determine the prediction results of the two methods in 60 min respectively. The details are as follows in Figure 8.

![Comparison Results of Rainfall Volume](image)

**Figure 8** Comparison Results of Rainfall Volume

The research shows that in 60 min, except that the CSI parameters of the LSTM algorithm model are slightly lower than those of the traditional optical flow method, the performance of LSTM model in the remaining POD and FAR is better than that of the optical flow method. Especially in FAR, the value of LSTM model is only 27.5 %, while the value of optical flow method is 38.2 %, with a difference of nearly 10 %, which indicates the superiority of LSTM model.

Based on the above conclusion, the LSTM radar echo model shows a good application effect in the comprehensive similarity of cloud images and the prediction accuracy of rainfall volume. Compared with other methods, it has certain advantages, indicating that this method has certain practical application value.

4. Conclusion
This research designed the radar echo model based on LSTM algorithm, explored the application of this model in dynamic weather forecasting technology, and mainly studied the evaluation results of this model in the comprehensive similarity of cloud images and the prediction of rainfall volume. The specific results of this research are as follows. In the analysis of the comprehensive similarity of cloud images, the comprehensive similarity of the extrapolated prediction of the model involved in this study at the 15th – 30th min was 87 %, 80 %, 76 % and 72 %, respectively, and the overall comprehensive similarity was relatively higher than others. In the prediction of rainfall volume, POD was 64.1 %, FAR was 20.6 %, and CSI was 43.8 %. With the passing of time, the value of FAR gradually increased, and the values of POD and CSI gradually decreased. By comparing with other algorithms, it can be seen that the comprehensive prediction results of the LSTM radar echo model were better than those of the edge corrosion expansion method, and the performance of the LSTM radar echo model in the prediction of rainfall volume was better than that of the optical flow method, especially in FAR with a difference of nearly 10 %. Based on the above research results, it can be seen that the algorithm designed in this study had a good application effect, and compared with the traditional algorithm, it had certain advantages and a good practical application effect. However, some methods still need to be improved in this research. In the follow-up researches, the model will be further optimized to improve its efficiency.

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