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Research on Agricultural Environment Prediction Based on Deep Learning

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Abstract

The environmental security of agriculture is closely related to human beings. Analytical training of agricultural environmental data, forecasting its development trend, has positive significance for the protection of the safety of agricultural products. This paper proposes an agricultural environment prediction model based on deep learning LSTM (Long Short-Term Memory). By analyzing the agricultural environment parameters of the current period, the environmental parameters of the next moment can be predicted to achieve the purpose of early warning. The experimental results show that the model's prediction results have little deviation from the actual values; on this basis, the LSTM model is optimized to replace LSTM with GRU(Gated Recurrent Unit), and the model is more effective.

Keywords: Deep learning; Agricultural environment;LSTM;GRU

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1. Introduction

Agriculture is a basic industry that affects the national economy and the people's livelihood. China's traditional agriculture is facing the need to ensure the total amount of agricultural products, adjust the structure of the agricultural industry, improve the quality of agricultural products,improve the efficiency of production, reduce resources, and environmental pollution problems.These problems lead to the situation that our country cannot meet the needs of sustainable agricultural development.Therefore,research on agricultural environmental prediction is imperative.Agricultural environmental information is time series data with diversity, variability and dispersal. It is a difficult task to analyze and predict data in the face of complex data types and complex time series of data structures.The LSTM (Long Short-Term Memory) in deep learning was proposed to satisfy this requirement and developed rapidly. As a special recursive neural network, LSTM can explore the nonlinear relationship between time series data, which is suitable for agricultural environmental time series prediction problems.

This paper presents an agricultural environmental prediction and analysis model based on LSTM algorithm. This paper uses LSTM to train the collected agricultural environmental data to predict the next agricultural environmental conditions,and optimizes LSTM by replacing LSTM with GRU, adding dropout layer to prevent overfitting,and use three statistics,MAE,MSE,RMSE,for comparative analysis.

2. Related work

According to domestic and foreign literature surveys, Baggio deployed a Wireless Sensor Networks for measuring humidity and temperature to reveal when the crop was at risk and let the farmer treat the plants only when really needed[1]. By studying the occurrence of wheat aphids over the years and related meteorological data, we used stepwise regression and wavelet neural network to predict the occurrence of wheat aphids[2]. Su Yifeng et al.used agricultural internet of things technology to collect air temperature and humidity, and constructed based on the support vector machine dynamic weather model[3].

In recent years, with the continuous development of deep learning technology, some deep learning models have been gradually applied to the research of time series data. Deep learning model is a deep neural network model with multiple non-linear mapping levels[4].It can abstract the input signal layer by layer and extract features to discover deeper underlying laws. In many variants of the RNN (recurrent neural network),the Long Short-Term Memory(LSTM)model compensates for problems such as gradient disappearance, gradient explosion, and lack of long-term memory in the RNN, making the recurrent nerve The network can really use long-range timing information effectively[5]. LSTM model has many successful application cases in the research of time series data in different fields, including language-related language modeling, speech recognition, machine translation[6], multimedia-related audio and video data analysis[7]. Picture title modeling[8],road transport-related traffic flow prediction[9],and Medical related protein secondary structure sequence prediction. However[10],in the field of agricultural environment, related studies based on deep learning have not yet found much.

Through investigation, we can see that the prediction of agricultural environment mostly uses traditional shallow models such as support vector machines and neural networks. The shallow model has strong dependence on features, its learning ability is limited, and it has a strong dependence on features of artificial extraction. Based on this, this paper collects and analyzes the collected agricultural data, and proposes to use the deep learning model to predict the agricultural environment and optimize it to enhance the learning ability of the prediction model.

3. Methodology

3.1. Data preprocessing

The experimental data comes from agricultural environmental monitoring data of the 2018 annual national key R&D project grain cloud platform project. First, the environmental monitoring data is cleaned and feature extraction, and the generated characteristic log data includes time series of environmental temperature, humidity, and the like. Then based on the collected data, the key factors affecting the agricultural planting process can be analyzed. The main parameters are temperature, humidity, pm2.5, air pressure, and wind speed and wind direction, as shown in Table1.Figure1 plots the key factors over time. Finally, the data set was transformed into supervised learning problems and normalized variables, which were processed according to the input format of LSTM to prepare for model training.

Table 1. Variable description

Variable	Description
temp	Temperature near farmland
humidity	Soil moisture
pm2.5	Pollution index near farmland
pressure	Pressure near farmland
wind speed	Pressure near farmland
wind direction	Wind direction near farmland

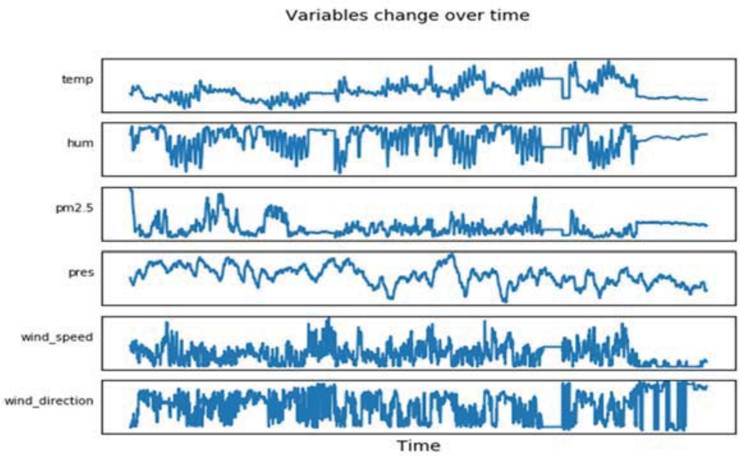


Fig. 1. Variables change over time

3.2. Model construction

3.2.1 LSTM

Compared with the traditional RNN,LSTM uses a gate mechanism to solve the problem of the gradient disappearing. It consists of three control gates and one internal memory cell. This paper designs a LSTM model for the current data set. The data provided by the project is used as training data and the input size is 20000*6 each time. If a missing value occurs, a zero-fill method is performed. The LSTM network is implemented using the Keras framework. There are 3 layers, the input layer is 1 input, the hidden layer has 50 neurons, and finally it is a fully connected layer. The output is the agricultural environment parameter at the next moment, ie 1*6. Dimension vector. The entire learning model is shown in the figure. The parameters used by our training network are: epochs=30, bacth_size=72.The model optimizer uses rmsprop. The mean square error mse was used to track the loss of the model on the training set and the test set.

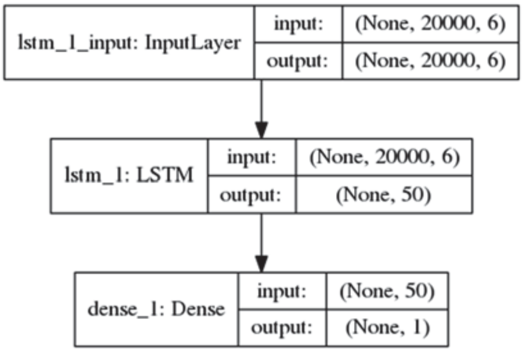


Fig. 2. Structure of LSTM

3.2.2 GRU

Based on LSTM,GRU is used instead of LSTM. Compared with the LSTM, the GRU unit has only two gates: a reset gate and an update gate, and there is no internal memory cell, GRU parameters are less, the amount of calculation is smaller, and the cost is more saved. The GRU model has 4 layers. The dropout layer is added to prevent the data from being over-fitted. Finally, it is a fully connected layer. The entire learning model is shown in the figure, and all other parameters are consistent with the LSTM model.

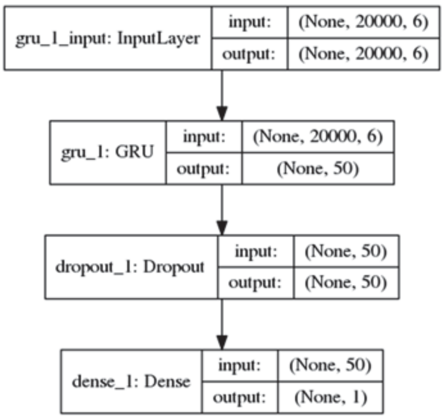


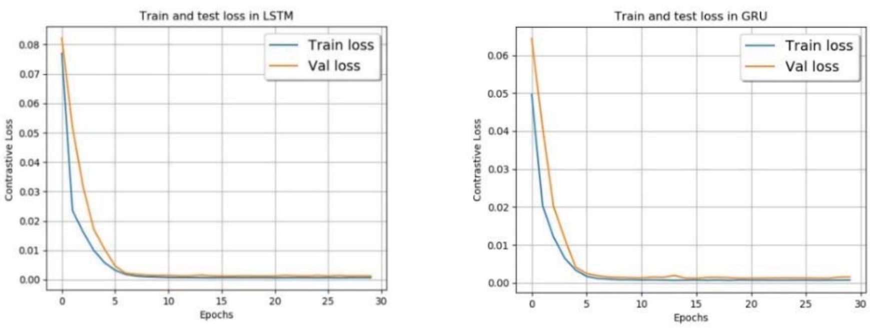
Fig. 3. Structure of GRU

3.2.3 Model evaluation

This paper selects the following three eigenvalues as a reference to evaluate the model. MAE is Mean Absolute Deviation, which is the average of the absolute values of the deviations of all individual observations from the arithmetic mean. The mean square error of MSE is the expected value of the square of the difference between the estimated value of the parameter and the true value of the parameter. The root mean square error of the RMSE is the square root of the ratio of the square of the observed value to the true value deviation and the number of observed times n. These three parameters are statistics commonly used in statistical learning to evaluate the prediction accuracy of the model.

4. Experimental results

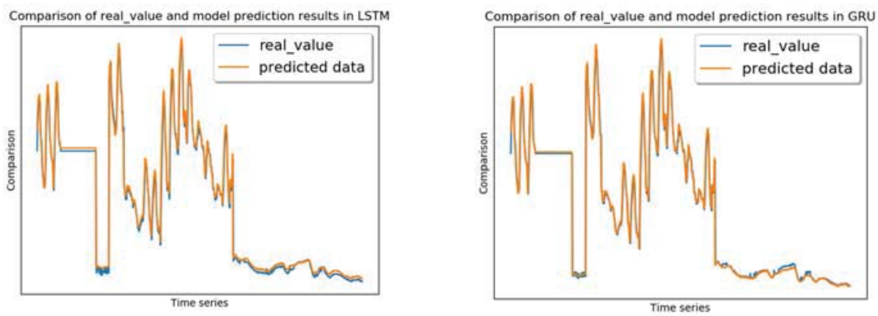
This article uses a cross-validation method to divide the training set and the test set from the raw data.Figure4 shows the loss of the LSTM and GRU models on the training set and the test set, respectively. As can be seen from the Figure4,the model loss of LSTM and GRU continuously decreases with the training period, and eventually they are all less than 0.005.On the LSTM, the test set loss is very close to the training loss, and it is prone to overfitting. On this basis, the LSTM is optimized, the GRU is replaced by the LSTM, the model structure is simpler, and the dropout layer is added at the same time to reduce overfitting. As can be seen in Figure4,the GRU initiated model loss is smaller than the LSTM model and the overfitting is effectively reduced.



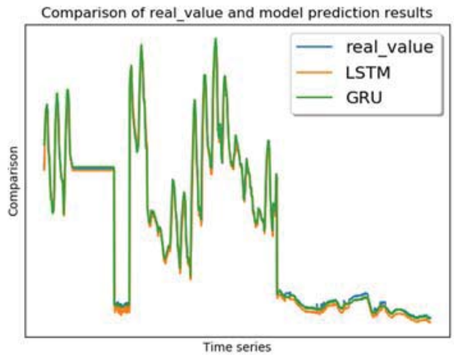
(a)LSTM (b)GRU

Fig. 4. Train and test loss

In this paper, the trained LSTM and GRU models are respectively used to make predictions on the test set. Figure5 shows that the prediction results fit well with the real value, and the model can accurately predict the agricultural environment. From Figure 5(c), we can see that compared with LSTM, the prediction results of GRU fit better with the real value.



(a)LSTM (b)GRU



(c) Comparison

Fig.5. Comparison of real_value and model prediction results

Figure6 shows how the three statistics, MAE, MSE, and RMSE, used in this paper evaluate the regression prediction results of LSTM and GRU models, respectively.MAE,MSE,RMSE are all lower the better.As can be seen from Figure6,the error between the predictions based on the LSTM and GRU models and the true values is very low,while the values achieved in others' work are high. In LSTM, MAE is 0.78, MSE is 2.12,RMSE is 1.45, while in GRU, MAE is 0.69, MSE is 1.89, RMSE is 1.37. We can compare the values of the two model, GRU's values are all lower.The improved GRU model is slightly better than the LSTM model in MAE, MSE, and RMSE.

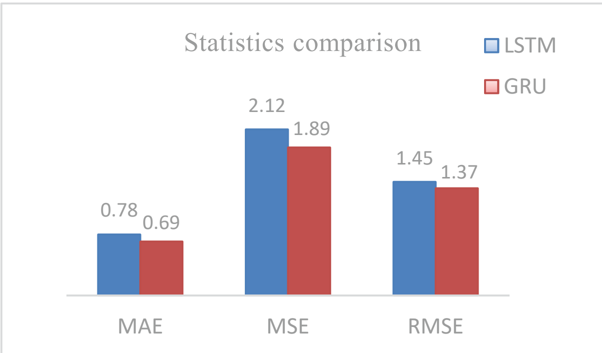


Fig.6. Statistics comparison

5. Conclusion

In agricultural cultivation, crops are affected by various environmental factors. This paper uses the LSTM based on deep learning to predict the agricultural environment. Through the parameters of agricultural environment in the current period, the environmental parameters in the next stage are forecasted so that agricultural preparation can be made in advance. By replacing the nerve layer, increaseing the drop layer , this paper improves the accuracy of the model. Combined with this model, we can further study the early warning points of the agricultural environment, add the agricultural environmental labeling system, and realize the input of the current environmental parameters to obtain the normal or abnormal environmental label at the next moment.

Acknowledgements

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