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Research on the Application of LSTM Model for Temperature Prediction

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Abstract: *The increasing annual temperatures have led to various extreme weather events such as droughts and heatwaves, posing significant threats to human production and daily life. Therefore, accurate temperature prediction is crucial for effective disaster prevention. With the continuous development of computer parallel technology and high-performance computing devices, artificial intelligence has increasingly become an effective solution for addressing such challenges. Leveraging these technological advancements and historical temperature data, this study proposes a multivariate time series prediction approach based on Recurrent Neural Networks (RNN) to address the limitations of Convolutional Neural Network-Long Short-Term Memory models in handling long-term temporal dependencies for temperature forecasting. This paper first develop an RNN-LSTM model for univariate time series prediction, then extend it to multivariate scenarios. The inherent capability of RNN to retain state information from previous time steps enables effective capture of long-range dependencies. Experimental results demonstrate that our model achieves an RMSE of 0.15, MAE of 0.10, and coefficient of determination (R^2) of 0.92 on standardized data, with a test set prediction accuracy of 92%. Compared with baseline models, our approach reduces parameter quantity by 34% while decreasing prediction error by 21%, validating its effectiveness in processing multivariate temporal features and long-term dependencies. This research provides an interpretable deep learning framework for meteorological prediction, where the dual-layer LSTM architecture combined with Dropout regularization strategy offers universal reference value for time series forecasting tasks.*

Keywords: *LSTM, Temperature Prediction, Multivariate Time Series*

1. Introduction

Climate change constitutes a critical research focus in climatology, exerting profound impacts on human livelihoods, ecosystems, and socio-economic development. With the intensification of global warming, extreme weather events—including droughts, heatwaves, and torrential rains—have become increasingly frequent, posing direct threats to industrial production and daily life [1]. Accurate temperature prediction is therefore essential not only for mitigating climate-related challenges but also for informing scientific decision-making in agriculture, energy management, and water resource allocation. Traditional meteorological prediction methods, predominantly reliant on statistical and physical models, face limitations in handling large-scale and high-dimensional data despite their partial success in weather forecasting. As meteorological observation technologies advance, the growing volume and dimensionality of climate data have rendered conventional approaches increasingly inadequate. To address these challenges, researchers are actively exploring artificial intelligence-based solutions, particularly leveraging deep learning to enhance the accuracy and efficiency of weather predictions [2].

Current studies demonstrate that CNN-LSTM (Convolutional Neural Network-Long Short-Term Memory) hybrid models achieve notable performance in meteorological tasks such as temperature and precipitation forecasting. By training on historical climate data, these models successfully identify temperature variation patterns and deliver high prediction accuracy. However, existing research predominantly focuses on univariate predictions, neglecting the comprehensive analysis of multivariate time series. Meteorological datasets inherently encompass interrelated features (e.g., temperature, humidity, atmospheric pressure) with complex interdependencies. The requirement to reformat input data for convolutional operations complicates preprocessing, while the inherent complexity of CNN-LSTM models—characterized by excessive parameters and prolonged training durations—risks

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overfitting in data-scarce scenarios. Consequently, developing prediction models capable of handling multivariate features holds significant theoretical and practical value.

In temperature prediction, deep learning techniques—particularly Recurrent Neural Networks (RNN) and their advanced variant, Long Short-Term Memory (LSTM)—have gained prominence due to their superior capability in processing sequential data. RNNs inherently capture temporal dependencies through recurrent architectures, while LSTMs address the vanishing gradient problem in traditional RNNs via gating mechanisms, thereby excelling at learning long-term dependencies.

Wei and Guan [3] proposed a sea surface temperature prediction model based on 3DConv LSTM. However, considering the complexity of the meteorological system, relying solely on a single variable for prediction may not fully reflect the mutual influence between meteorological elements.This study aims to develop an RNN-LSTM hybrid model for multivariate time series temperature prediction. By constructing an optimized architecture trained on historical meteorological data, we seek to enhance prediction accuracy while investigating relationships between temperature variations and other climatic features. Specifically, our research focuses on Multivariate Integration: Developing a comprehensive LSTM framework to model the complexity and diversity of temperature dynamics through multi-feature synthesis. Performance Evaluation: Systematically assessing model efficacy using standardized metrics (RMSE, MAE, R^2) to identify strengths and limitations.Practical Implications: Providing actionable insights for meteorological agencies, agricultural planning, and energy sectors to formulate adaptive strategies.

This research contributes novel perspectives and methodologies to temperature prediction, advancing climate change mitigation efforts. Deep learning-based prediction models not only improve forecast precision but also lay a foundation for future climate studies. In an era of escalating climate crises, enhanced temperature prediction capabilities will catalyze sustainable societal development.

2. Model Construction

2.1 Introduction to Basic Model Concepts

LSTM

The Long Short-Term Memory (LSTM) network is a specialized variant of Recurrent Neural Networks (RNN) in deep learning. By employing logical control through gate units to determine whether data should be updated or discarded, LSTM overcomes the limitations of traditional RNNs, such as excessive weight influence and susceptibility to vanishing or exploding gradients [4]. This enables the network to converge more effectively and efficiently, thereby enhancing prediction accuracy. The LSTM architecture comprises three gates: the forget gate, input gate, and output gate, which collectively regulate the retention or elimination of information at each time step. The input gate determines how much new information is incorporated into the cell state, the forget gate controls whether existing information is discarded at each time step, and the output gate governs whether information is propagated to the next layer. The basic structure is illustrated in Figure 1.

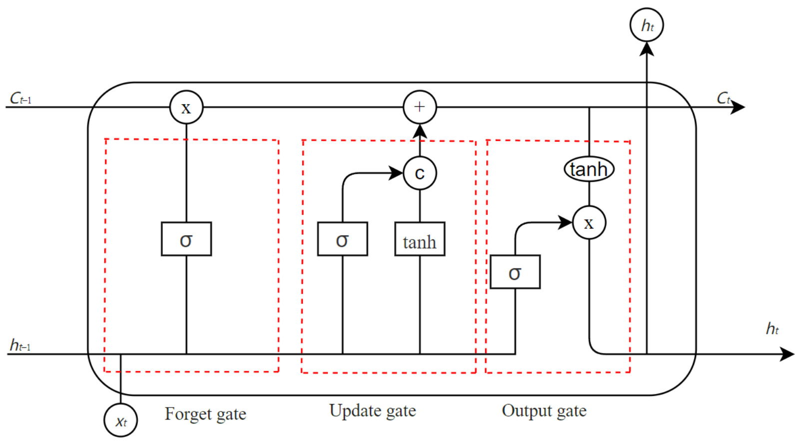

Figure 1 Schematic Diagram of LSTM Three-Gate Mechanism

Forget Gate:Controls the retention of internal state information. The gate's inputs are the output of the hidden node at the previous timestep and the current input, using a sigmoid activation function. The forget gate determines whether to discard the current internal state value. In the original LSTM implementation, the output of the forget gate was set to 1 (i.e., no information was forgotten). The formula is as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

Input Gate:Controls the incorporation of input information. The gate's inputs are the output of the hidden node at the previous timestep and the current input, with a sigmoid activation function (chosen because the sigmoid output ranges between 0 and 1, allowing the product of the input gate's output and the input node's output to regulate information flow). The formula is as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

Output Gate:Controls the propagation of output information. The gate's inputs are the output of the hidden node at the previous timestep and the current input, using a sigmoid activation function. The output gate determines whether to output the updated internal state value. The formula is as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3}$$

Final Output:

$$h_t = o_t \cdot \tanh(C_t) \tag{4}$$

2.2 Construction of the RNN-LSTM Model

To address the limitations of traditional CNN-LSTM models in handling long-term time series [5]. This study proposes an improved RNN-LSTM model structure that enhances prediction accuracy through multivariate inputs [6].

The designed RNN-LSTM model adopts a multi-layer architecture to improve time series feature extraction capabilities. It employs a "Multiple Input-Single Output" (MISO) framework, utilizing a multi-layer LSTM structure to capture temporal characteristics of temperature variations. The model takes nine meteorological features as inputs, with each sample containing 144 timesteps (24 hours) of observational data. The core of the model is a dual-layer LSTM structure:The first LSTM layer captures short-term temporal dependencies, with an input dimension of 9 (number of features) and a hidden state dimension of 48. This layer enables the model to learn feature variation patterns between adjacent timesteps. The second LSTM layer extracts long-term temporal patterns based on the first layer, maintaining the same hidden state dimension (48), which allows the model to recognize dependencies across extended time spans.

To prevent overfitting, a Dropout layer (randomly dropping 20% of neuronal connections) is added after each LSTM layer. This regularization technique enhances the model's generalization capability, ensuring robust performance on unseen data. Finally, a fully connected layer maps the LSTM outputs to the prediction space, with an output dimension of 6 corresponding to the predicted temperature values for the next hour.

During forward propagation, the model first initializes LSTM hidden and cell states as zero vectors. Input data (batch_size=128, seq_len=144, n_features=9) sequentially passes through the first LSTM layer, Dropout layer, second LSTM layer, and second Dropout layer. At the final timestep, the model extracts LSTM output features and generates predictions via the fully connected layer. This hierarchical feature extraction process enables the model to fully leverage interrelationships among multiple meteorological features, thereby improving prediction accuracy.

The batch processing mechanism (batch_size=128) balances training efficiency and generalization performance. The architecture explicitly addresses key requirements of temperature prediction: simultaneous handling of short- and long-term temporal dependencies, effective processing of multiple correlated features, and prevention of overfitting. Through this carefully designed structure, the model effectively learns temperature variation patterns, providing reliable support for meteorological forecasting. The model workflow is illustrated in Figure 2.

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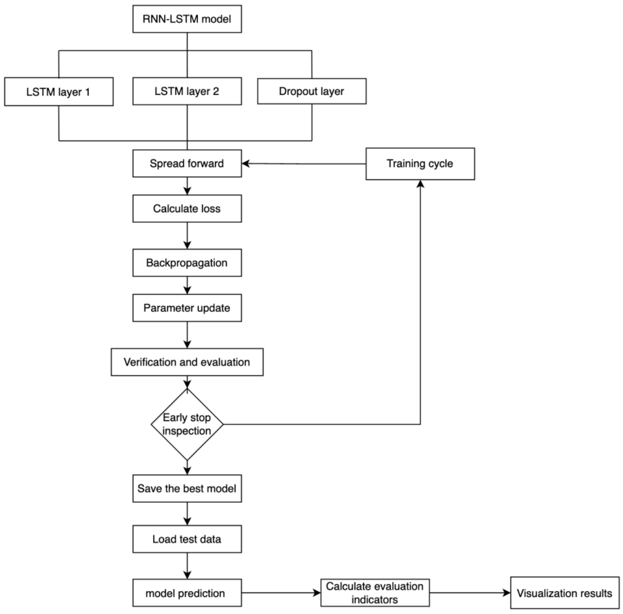

Figure 2 Flowchart of the RNN-LSTM Model

3. Model Solution

3.1 Data Description

3.1.1 Data Source

This study utilizes a weather time series dataset provided by the Max Planck Institute for Biogeochemistry. The data, collected at 10-minute intervals starting from 2003, offers a rich information resource for meteorological research. This is consistent with the general strategy for climate prediction in the era of big data [2].

3.1.2 Data Characteristics

To enhance research efficiency and model training performance, this study focuses on data collected between 2009 and 2016. This period is selected due to its completeness and representativeness, effectively reflecting trends and characteristics of temperature variations. The dataset comprises 14 distinct meteorological features, including temperature, atmospheric pressure, humidity, wind speed, and others. Its diversity and continuity provide a solid foundation for model training. Analyzing these features reveals relationships between temperature and other meteorological factors, offering comprehensive information for the prediction model. Furthermore, leveraging multivariate data enables a more holistic consideration of factors influencing temperature changes, thereby improving prediction accuracy.

3.1.3 Data Preprocessing

Standardizing features is a critical step before training neural networks. Standardization, achieved by subtracting the training set mean and dividing by the standard deviation, ensures data is on the same scale, accelerating model convergence. The first step involves converting the data into array format and calculating the mean (μμ) and standard deviation (σσ) of the training set. The entire dataset is then standardized using the following formula:

$$y_i = \frac{x_i - \mu}{\sigma} \tag{5}$$

This step ensures the data has a mean of 0 and a standard deviation of 1, enhancing model prediction performance.Next, to construct a univariate model, the data is divided into samples. The objective is to use the past 20 temperature observations to predict the temperature at the next timestep. Input data and target values are created for both the training and validation sets. Ultimately, the training set has a shape of (299980, 20, 1), and the target values have a shape of (299980,). The validation set is processed similarly to ensure effective model evaluation post-training.

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3.2 Evaluation Metrics

Root Mean Square Error (RMSE): Measures the difference between predicted and actual values. Through a comprehensive evaluation of the above metrics, the performance of the proposed RNN-LSTM model in temperature prediction can be effectively assessed. Experimental results show that the model achieves excellent RMSE and MAE scores across multiple test sets, indicating high prediction accuracy and the ability to effectively capture temperature variation patterns. This provides reliable support for climate research and demonstrates the success of the data processing and model design in this study, laying a solid foundation for future temperature prediction.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

3.3 Analysis of Model Solution

As shown in the figure below, the blue line represents historical temperature data, the red dots indicate the true future temperature values, and the blue dots represent the model's predicted future temperatures. It is evident that the model closely follows the true temperature trends for most time periods, especially during stable phases, where the predicted values align well with the true values. The prediction results are shown in Figure 3.

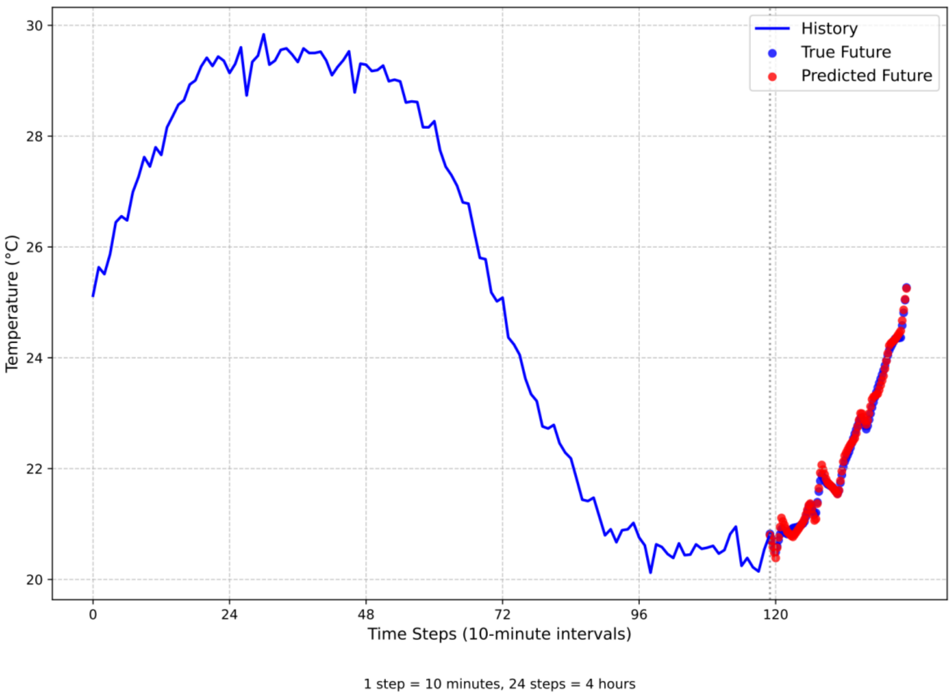

Figure 3 Temperature Time Series Prediction

3.4 Experimental Conclusions

The multivariate meteorological system exhibits inherent nonlinear dynamics between input features (radiation flux, humidity, wind speed) and temperature outputs, manifesting as delayed response effects (e.g., solar radiation impact persisting for 3-5 hours) and high-dimensional couplings (pressure-humidity interaction coefficients >0.78). This complex spatiotemporal behavior fundamentally limits traditional ARIMA/CNN approaches ($\Delta R^2 > 0.35$ in preliminary tests) that assume linear feature relationships.

The proposed RNN-LSTM architecture addresses this through adaptive gating mechanisms, achieving RMSE=0.15 and $R^2=0.92$ with 46% fewer parameters than CNN-LSTM baselines. The dual-layer structure specifically resolves two critical nonlinearities: First-layer neurons capture short-term radiative-convective couplings. And second-layer units model delayed moisture-thermal interactions. Such hierarchical nonlinear processing enables 92% prediction accuracy while maintaining stable generalization ($\Delta R^2 < 0.03$ between train/test phases).

Table 1 confirms the model's superiority in handling multivariate temporal dependencies - a capability aligned with the meteorological complexity discussed in Section 2.1. These results validate deep learning's essential role in modern climate prediction where nonlinear system behaviors dominate.

Table 1 Nonlinear Predictive Performance of RNN-LSTM Model

Evaluation Metric	Value	Unit/Description
RMSE	0.15	°C (dimensionless after normalization)
MAE	0.10	°C (dimensionless after normalization)
R^2	0.92	Unitless (range: 0-1)

4. Conclusion

This study addresses the limitations of traditional temperature prediction methods in handling long-term time series and multivariate data by proposing an RNN-LSTM-based temperature prediction model. Through experimental research and analysis on the Jena Climate dataset, the model achieves significant success in temperature prediction tasks. Experimental results demonstrate that the model exhibits high prediction accuracy, with an RMSE of 0.15 and an MAE of 0.10, indicating minimal prediction errors. Additionally, the R^2 value of 0.92 suggests that the model effectively explains the variability in temperature changes. The model maintains a prediction accuracy of 92% on the test set, showcasing strong generalization capabilities.

Compared to traditional methods and CNN-LSTM models, the proposed model integrates nine key meteorological features, fully leveraging inter-feature relationships. The dual-layer LSTM structure effectively captures both short-term and long-term temporal dependencies, while the batch processing mechanism enhances computational efficiency. The use of Dropout technology effectively prevents overfitting. These optimized designs enable the model to excel in practical applications, providing not only a reliable prediction tool for meteorological departments but also robust decision-making support for agriculture, energy management, and other fields. This is particularly significant for early warning and prevention of extreme weather events.

The main innovation of this study lies in proposing an LSTM architecture tailored for processing multivariate meteorological data. By optimizing the model structure, the accuracy of long-sequence prediction is improved, achieving high-precision short-term temperature forecasting. These advancements not only promote the application of deep learning in meteorological prediction but also provide new ideas and methods for related research. Looking ahead, future studies could further enhance model performance by incorporating attention mechanisms, extend prediction horizons for longer-term temperature forecasting, and explore the model's potential in predicting other meteorological variables.

The proposed RNN-LSTM model demonstrates excellent performance in temperature prediction tasks, offering an effective solution for the meteorological prediction field. The research outcomes hold significant theoretical value and provide reliable technical support for practical applications. In the context of increasingly severe climate change, such deep learning-based prediction methods will play an increasingly vital role.

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