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Temporal Weather Forecasting and Analysis Using Recurrent Neural Networks and Long Short-Term Memory Based on Deep Learning

Dr. M. Meena Krithika,
Assistant Professor, Department of Computer Science with DA, N.G.M College, Pollachi,
Dr. E. RamaDevi
Associate Professor, Department of Computer Science with DA, N.G.M College, Pollachi,
Dr. A. Albina
Assistant Professor, Department of Computer Science with DA, N.G.M College, Pollachi,

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ABSTRACT

Weather forecasting plays a critical role in numerous sectors, including agriculture, transportation, and disaster prevention, and has therefore attracted increasing attention from the machine learning research community. This paper proposes a weather forecasting model that integrates Long Short-Term Memory (LSTM) networks within a Recurrent Neural Network (RNN) framework to improve prediction accuracy for time-series meteorological data. By exploiting the distinctive gating mechanisms of LSTM, the proposed model is capable of effectively learning long-term temporal dependencies, thereby alleviating the limitations of traditional RNNs in handling extended sequences. Experimental results demonstrate that the proposed approach significantly outperforms conventional forecasting methods in terms of prediction accuracy, with notably reduced error margins. In addition to validating the effectiveness of LSTM for weather prediction tasks, this study provides insights into the internal mechanisms of LSTM-based sequence modeling. The findings contribute to a deeper understanding of sequence prediction techniques and offer a foundation for addressing more complex forecasting challenges in future research. Overall, the integration of LSTM into the RNN architecture represents an important step toward enhancing the reliability and precision of data-driven weather forecasting models.

Keywords: LSTM, RNN, Weather Forecasting, Sequence Prediction

1. INTRODUCTION

With the rapid development of deep learning technologies, increasingly complex geophysical phenomena can now be analyzed and understood through data-driven approaches. Numerical simulation and predictive modeling have become essential tools for uncovering the underlying of atmospheric processes [1]. At the core of modern weather forecasting services lies numerical prediction, where forecasting accuracy is largely dependent on the precision of numerical models [2]. Over the past five decades, extensive efforts have been devoted to improving weather prediction techniques, accompanied by the construction of large-scale observational networks that provide abundant meteorological data to enhance forecast reliability [3].

Meteorological processes are inherently complex, exhibiting strong temporal and spatial variability. Nonlinearity, multiscale interactions, and uncertainty in parameter estimation pose persistent challenges to traditional physical modeling approaches [4]. With the rise of deep learning, neural networks have emerged as powerful tools for handling such complexity in forecasting tasks. Various neural network architectures have been developed, including feed forward neural networks, back propagation neural networks, and recurrent neural networks (RNNs), each possessing distinct structural characteristics and predictive capabilities [5].

Despite their advantages, traditional sequence prediction methods and standard RNNs suffer from notable limitations. Many approaches rely solely on numerical measurements and

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struggle to effectively capture long-term dependencies in time-series data. In particular, conventional RNNs are prone to gradient vanishing and explosion problems during training, which hinders their ability to learn from long sequences [6]. To address these shortcomings, Long Short-Term Memory (LSTM) networks were introduced as a specialized RNN architecture capable of selectively retaining and discarding information through gating mechanisms [7].

LSTM networks employ input, forget, and output gates to regulate information flow, enabling more robust learning, memory retention, and sequence modeling [8]. Compared with standard RNNs, LSTMs demonstrate superior performance in mitigating gradient-related issues and extracting meaningful temporal patterns. These advantages have led to widespread adoption of LSTM networks in sequential data analysis and forecasting applications. In this study, a data-driven deep learning approach is adopted to perform weather sequence prediction by integrating LSTM into an RNN-based forecasting framework [9].

To further enhance prediction accuracy using historical weather data, this research utilizes an open-source dataset from Kaggle and follows a systematic experimental workflow. The process includes data preprocessing, dataset partitioning, model construction with stacked LSTM layers and dropout regularization, model compilation using the Adam optimizer and mean squared error loss, and comprehensive evaluation through visualization and quantitative analysis. Experimental results indicate that the proposed RNN–LSTM model achieves higher accuracy and efficiency than traditional forecasting methods, particularly in predicting temperature and humidity trends.

2. LITERATURE REVIEW

2.1 RECURRENT NEURAL NETWORK (RNN)

A recurrent neural network (RNN) is the type of **artificial neural network** (ANN) that is used in Apple's Siri and Google's voice search. RNN remembers past inputs due to an internal memory which is useful for predicting stock prices, generating text, transcriptions, and machine translation.

In the traditional neural network, the inputs and the outputs are independent of each other, whereas the output in RNN is dependent on prior elementals within the sequence. Recurrent

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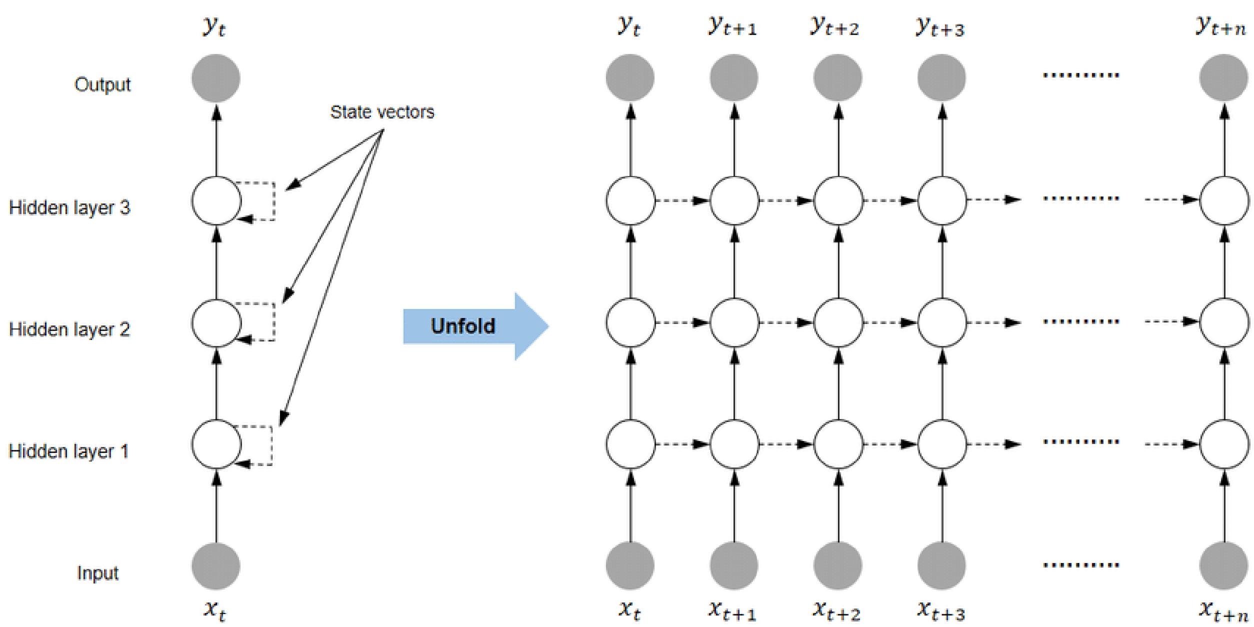
networks also share parameters across each layer of the network. In feed forward networks, there are different weights across each node. Whereas RNN shares the same weights within each layer of the network and during **gradient descent**, the weights and basis are adjusted individually to reduce the loss.



The image above is a simple representation of recurrent neural networks. If we are forecasting stock prices using simple data [45,56,45,49,50,…], each input from **X0** to **Xt** will contain a past value. For example, **X0** will have 45, **X1** will have 56, and these values are used to predict the next number in a sequence.

2.2 LONG SHORT-TERM MEMORY MODEL

LSTM was introduced by Hochreiter and Schmidhuber in 1997.The model is a robust recurrent neural network specifically designed to address the exploding and vanishing gradient issues that commonly occur when learning long-term dependencies, even with substantial time lags. Overall, this issue can be mitigated by employing a constant error carousel (CEC), which preserves the error signal within each unit's cell. Notably, these cells function as recurrent

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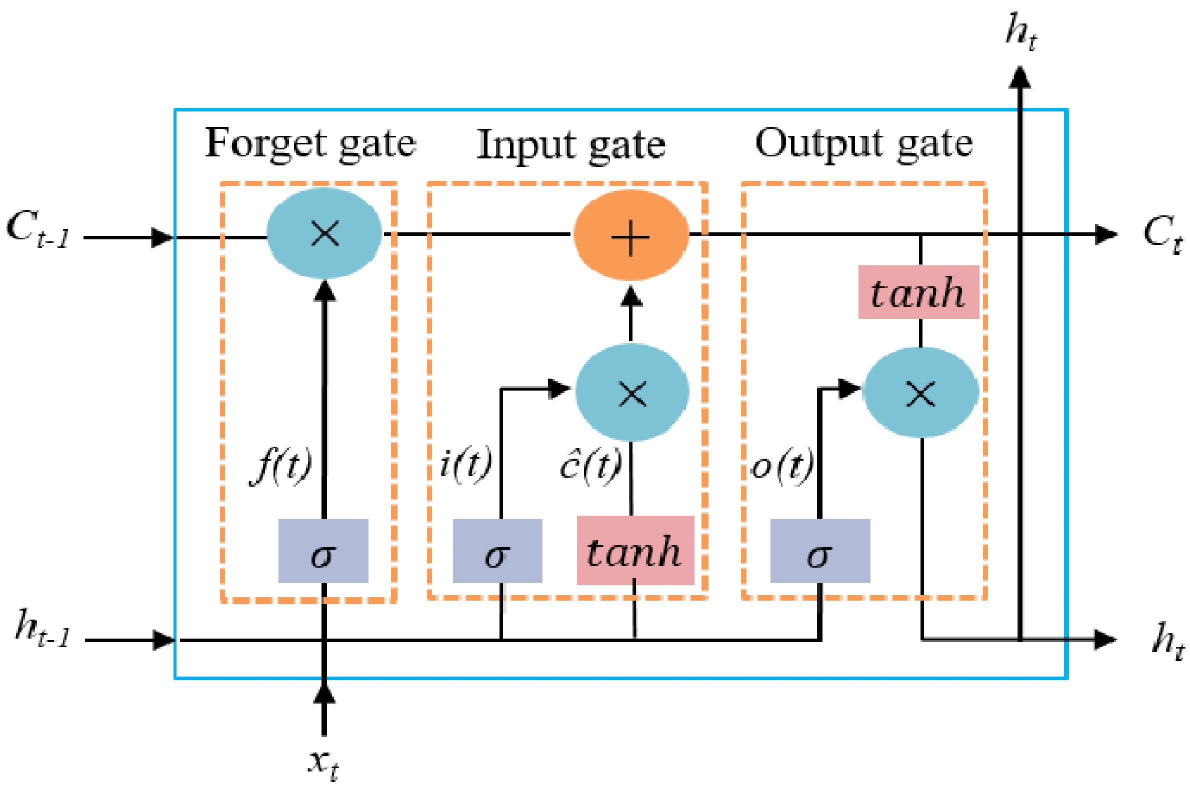
networks themselves, enhanced by the addition of an input gate and an output gate, collectively forming the memory cell. The self-recurrent connections provide feedback with a lag of one time. A standard LSTM unit consists of a cell, an input gate, an output gate, and a forget gate. The forget gate was not part of the initial design of LSTM, but was added by in order that the network will be able to reset its state. The cell retains values over arbitrary time intervals, while the three gates control the flow of information related to the cell. This is a simple LSTM model architecture with the gates, input, and output.



3. METHODOLOGY

3.1 DATASET DESCRIPTION AND PREPROCESSING

The dataset used in this study was obtained from Kaggle [10] and contains daily weather records spanning approximately four years. The dataset includes attributes such as date, precipitation, maximum temperature, minimum temperature, wind conditions, and categorical

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weather states (drizzle, rain, sun, snow, and fog). The relatively long temporal coverage provides sufficient data support for training and evaluating sequence prediction models.

For model development, the dataset was divided into three subsets. The first 800 samples were used for training, the subsequent 200 samples were allocated for validation, and the remaining samples constituted the test set. To meet the input requirements of the LSTM model and better represent temporal dynamics, the original two-dimensional data array was reshaped into a three-dimensional format. This format consists of the number of samples, the number of time steps, and the number of features. In this study, the feature dimension was set to one, indicating that each time step represents a single variable.

3.2 PROPOSED APPROACH

The proposed weather forecasting approach integrates the strengths of RNN and LSTM architectures. While RNNs are effective in processing sequential data, they struggle with long-term dependency learning. LSTM networks address this limitation through dedicated memory units and gating mechanisms, making them particularly suitable for extended time-series analysis.

In the proposed framework, data preprocessing is first performed to ensure compatibility with the model. The network architecture consists of four stacked LSTM layers, each containing 50 units, enabling the model to capture long-term dependencies and hierarchical temporal features. Stacking multiple LSTM layers forms a deep recurrent neural network that enhances the model's capacity to learn complex patterns from weather data.

To reduce over fitting and improve generalization, a Dropout layer with a rate of 0.2 is applied after each LSTM layer, randomly disabling 20% of the connections during training. Following the LSTM layers, a fully connected dense layer with a single output unit is employed to generate continuous-valued predictions, specifically temperature values.

The model is compiled using the Adam optimizer, which adaptively adjusts learning rates during training, and the mean squared error (MSE) loss function to quantify prediction errors. Model training is conducted using the training set, while performance is monitored on the

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validation set. During each training epoch, network weights are updated based on the loss function feedback, leading to progressively improved prediction accuracy.

3.3 LSTM ARCHITECTURE

LSTM is a widely used RNN variant designed to process and learn from sequential data. Unlike traditional RNNs, LSTM introduces a cell state and three key gating mechanisms: the forget gate, input gate, and output gate. These components allow the network to selectively retain useful information and discard irrelevant data over time.

At each time step, the forget gate determines which information from the previous cell state should be removed, while the input gate controls which new information should be added. The output gate regulates how much of the internal cell state is exposed as the hidden state output. This architecture enables LSTM networks to effectively capture long-term dependencies and significantly alleviates gradient vanishing and explosion problems.

In this study, the LSTM architecture allows the model to extract meaningful temporal features from historical weather data, resulting in more accurate and stable predictions.

3.4 LOSS FUNCTION

The selection of an appropriate loss function plays a crucial role in effective model training, particularly for sequence prediction tasks where the objective is to minimize the difference between predicted and actual values. In this study, the Mean Squared Error (MSE) is employed as the loss function to evaluate model performance. MSE measures the average squared difference between the predicted values and the corresponding actual observations, and it is mathematically defined as **MSE=n1∑i=1n(zi−yi)^2** The squaring of errors ensures that larger deviations are penalized more heavily, encouraging the model to reduce significant prediction errors during training. A lower MSE value indicates better prediction accuracy and improved model performance

3.5 IMPLEMENTATION DETAILS

The experiments were implemented using Python 3.11. Key hyper parameters include a window size of zero, 50 LSTM units per layer, and a Dropout rate of 0.2. Data visualization was performed using the matplotlib and seaborn libraries to facilitate interpretation of prediction results and present findings in an accessible manner.

4. RESULTS AND DISCUSSIONS

The proposed RNN–LSTM model was evaluated using a dataset covering approximately 1,500 days. Prediction results were compared against actual temperature values for both validation and test sets. The model demonstrates strong predictive performance, with predicted curves closely tracking observed temperature trends.

The validation results indicate that the model effectively captures temporal patterns, largely due to the stacked LSTM architecture and gating mechanisms. While occasional deviations occur during periods of high variability—likely influenced by external or unmodeled factors—the overall fit remains strong. Similar behavior is observed in the test set, suggesting good generalization capability.

Analysis of the loss curves reveals rapid convergence during training, with both training and validation losses decreasing steadily and stabilizing at low values. The close alignment between the two curves indicates minimal overfitting and robust learning behavior. These results confirm that LSTM-based architectures are well-suited for large-scale time-series learning and weather prediction tasks.

5. CONCLUSION

This study demonstrates that integrating LSTM networks within an RNN framework significantly enhances weather forecasting performance. Experimental results confirm that LSTM's memory and gating mechanisms enable effective learning from long-term historical data,

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resulting in accurate and stable temperature predictions. The use of stacked LSTM layers further improves the model's capacity to handle complex temporal patterns.

Future research may incorporate additional meteorological variables, external influencing factors, and advanced techniques such as model fusion or ensemble learning to further improve prediction accuracy. Data augmentation and statistical feature analysis may also enhance robustness in scenarios with limited or imbalanced data. Overall, the proposed approach provides a reliable and extensible foundation for data-driven weather forecasting and other sequence prediction applications.

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