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Implementation of Long Short Term Memory Algorithm for Rainfall Prediction of East Madhya Pradesh, India

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Abstract
Rainfall is an important factor in Madhya Pradesh state as the economy is dependent on agriculture here. Time Series forecasting approach of univariant data for monthly rainfall prediction is done using Long Short Term Memory [LSTM]. To judge the accuracy of models two parameters were chosen one for error and another for accuracy i.e. Root mean square error (RMSE) and Cosine similarity (CS). Long short term memory model applied on 1404 monthly data of east Madhya Pradesh state. Various epoch(s) such as 15, 30, 45, 60, 75 and 90 respectively are done for LSTM approach. The computed value of RMSE was found as 0.1142, 0.0895, 0.1042, 0.1042, 0.0612, 0.0798 and 0.0673 respectively. Likewise, value of CS was found as 0.9628, 0.9778, 0.9762, 0.9812, 0.9776 and 0.9795 respectively. The experimental results show that Long Short Term Memory gave significant results in lower epochs.

Keywords: LSTM, Bi-LSTM, deep learning, prediction, rainfall

1. Introduction

Rainfall is the output of condensation of water vapor and precipitation, results in forming droplets that fall from clouds due to gravitational force. It is vital part of the water cycle and is a crucial atmospheric process that is very difficult to forecast because of complex weather system [1]. Various activities related to society, including agricultural sector, construction sector, government sector, electricity production etc. are directly or indirectly affected by rainfall [2]. Precipitation is one of the most important factors, affecting the natural phenomenon by flood, draught, landslide and avalanches etc. [3-7]. Nowadays machine learning and artificial intelligence applications based are in trend. Deep learning is a part of machine learning which provide high accuracy in comparison with neural network [8]. Several deep learning approaches gave outperform results in different applications. Time series data based on deep learning model have been applied in various fields like traffic flow detection, fraud detection, video surveillance etc. This paper focuses on Madhya Pradesh state, India. The paper aims to use LSTM model for the prediction of rainfall uni-variate time series data.

The concept of Artificial Neural Networks (ANN) plays a vital role in forecasting, and a suitable neural network approach for data analysis is to be chosen. Various categories of neural networks are their like Feed forward neural networks, Back propagation neural networks, Convolution neural network, Recurrent neural networks, etc. for forecasting. Recurrent neural network are the suitable option to deal with rainfall data as it handles time series data effectively.

Deep learning has achieved a great potential for solving the complex nonlinear problem by encapsulating the nonlinearities of various deep neural network [9]. For rainfall forecasting approach it should be of great potential, capable to capture temporal and spatial structure, so ConvLSTM based architecture is used [10-12]. A prediction model for cloud scaling was developed [13]. Multivariate Fuzzy-LSTM (MF-LSTM) was built to predict the consumption of multivariate data. LSTM based Differential RNN (dRNN) was modeled [14] for crowd scene analysis. Some LSTM based enhanced mode like Bidirectional LSTM are discovered [15]. To elaborate the memory of LSTM through each N-dimension and Grid LSTM came with a solution by minimizing the computation of output memory vectors [16]. Grid LSTM, approach provides a solution by changing the complexity of output memory vectors [17]. LSTM proves its superiority in various aspects, the problem of varnishing gradient is removed by LSTM techniques.

1.1. Data Collection

A time-series monthly rainfall data of Madhya Pradesh State from January 1901 to December 2017 was collected. In all, monthly rainfall data of 1404 months were collected. The data has been downloaded from the official website of the Indian Metrological Department (IMD). The geographical locational of MP East

2. Model Used

2.1. Long Short Term Memory Model

The ability to learn the relationship in a long range of manner, is known as LSTM model, and is a type of RNN method.

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LSTM is invented by Hochreiter & Schmidhuber in 1997. LSTM has three gates input gate, output gate and forgot gate. Input gate works to checks whether the information is useful or not for storing the data in memory. Forget gate is used to forget about the previous unnecessary information and to carry fruitful information [18-19].

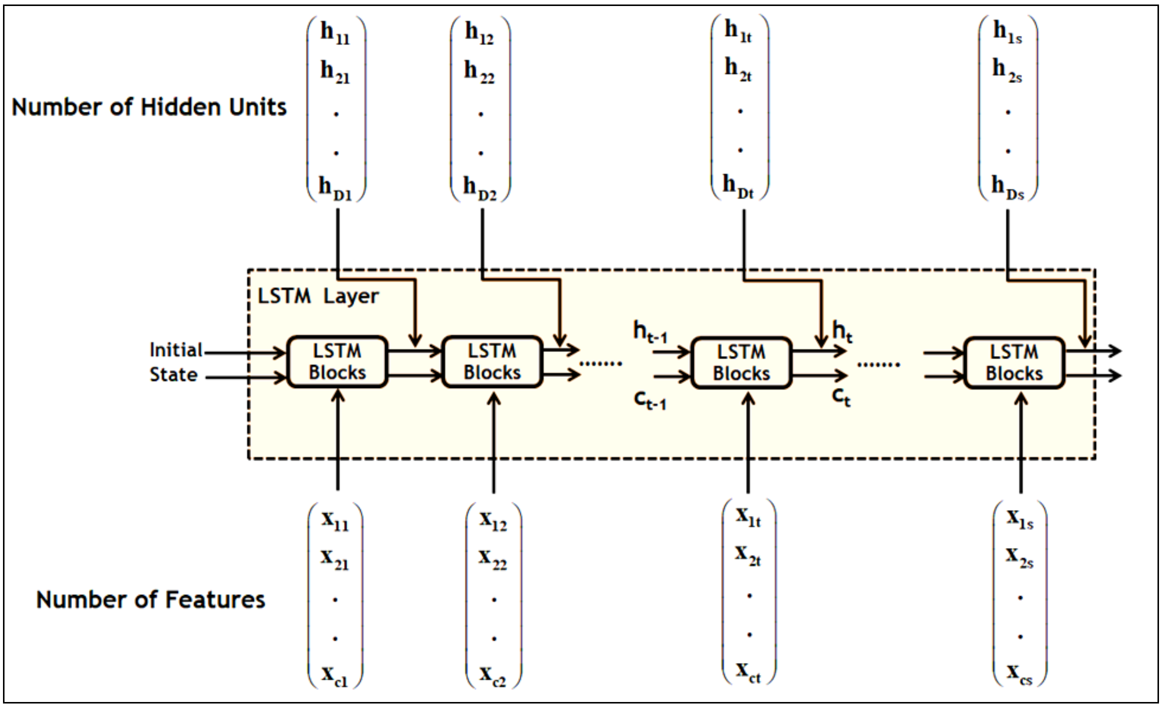

Fig 1: Lstm Neural Network Architecture

For long time remembering information LSTMs are excellent. LSTM Modules has three different gates and activation function σ as depicted in Fig. 01. The symbol π and Σ represent element wise multiplication and addition respectively.

The calculation procedure for the Block of LSTM block is as under:-

The input value can only be preserved in the state of the cell if the input gate permits it. The input value of i_t and the candidate value of the memory cells $\tilde{C}_t$ at time step, t, is calculated as follows:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{1}$$

$$\tilde{C}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{2}$$

Where W, U, b represents the adjustable weight matrices and adjustable bias vector, respectively and σ is the sigmoidal function. The weight of the state unit is managed by the forget gate and the value of forget gate is computed as

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{3}$$

The new state of memory cell is updated as

$$C_t = i_t \times \tilde{C}_t + f_t \times C_{t-1} \tag{4}$$

With the new state of memory cell, the output value of the gate is calculated as follows:

$$O_t = \sigma(W_0 x_t + U_0 h_{t-1} + V_0 C_t + b_0) \tag{5}$$

The final output value of cell is defined as

$$h_t = o_t \times \tanh(C_t) \tag{6}$$

3. Result & Discussion

A time series uni-variant dataset was used to predict monthly rainfall by applying LSTM model. Factors for judging the accuracy criteria of prediction were Root Mean Square Error (RMSE) and Cosine Similarity (CS). We start experimenting for various epoch(s) like 15, 30, 45, 60, 75 and 90 respectively. The value for RMSE needs to be less for obtaining accurate prediction quality. On the other hand, the value of Cosine similarity (CS) must be nearer to 1, if possible we consider that the actual and the predicted data are same.

If we observe Table 01 for various epoch(s), we find that the value of RMSE is 0.0612 for 60 epochs, which is smallest in comparison to that of prediction result obtained for rest of the epochs. We also got the value of Cosine similarity as 0.9812 respectively which is again highest for 60 epochs. When we observed Table 01 for 70 epoch(s) and 90 epoch(s) we find that the errors are increasing and the value of cosine similarity are reducing. This is an indication that prediction results are better for lower epoch(s) i.e, 60 epochs as compared to higher epoch(s). Graph obtained for (epoch = 60) are shown in Figure 2. In these figures, a great resemblance between the actual and forecast data can be observed.

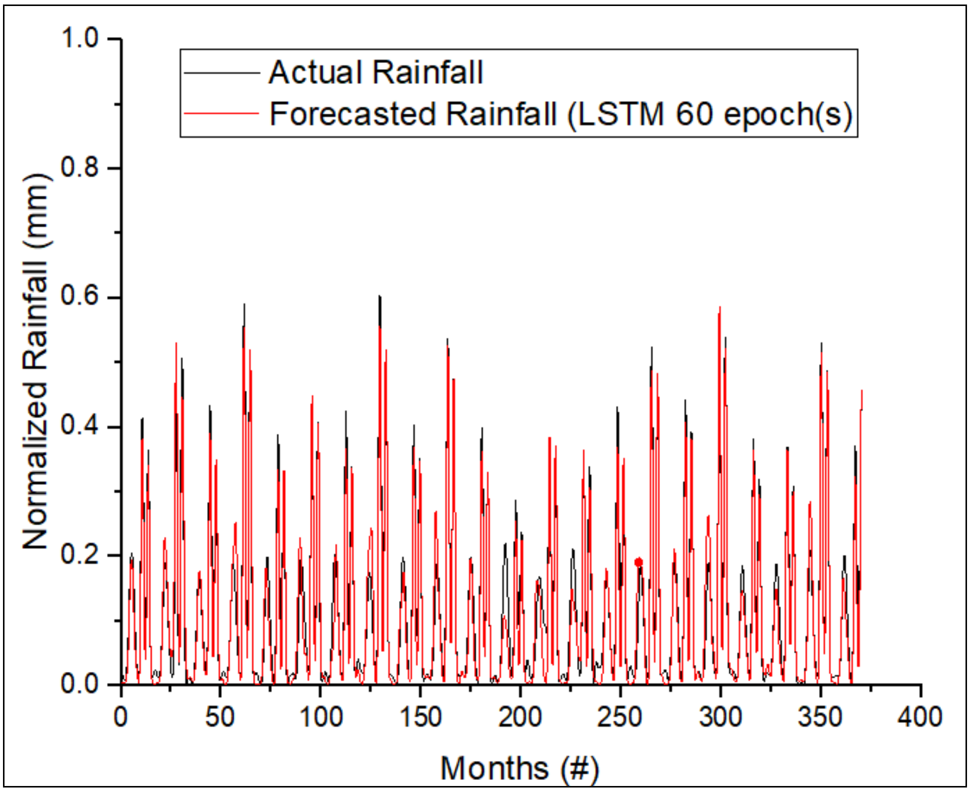

Fig 2: Comparison between Actual & Forecast Rainfall (60 epoch(s) using LSTM algorithm

Table 1: LSTM based analysis of time series data

Number of Epoch(s)	Parameters Calculated	
	RMSE	CS
15	0.1142	0.9628
30	0.0895	0.9778
45	0.1042	0.9762
60	0.0612	0.9812
75	0.0798	0.9776
90	0.0673	0.9795

4. Conclusion

In present research paper, Deep learning approach for rainfall forecasting based on the time series analysis is incorporated using PYTHON Version 3.8. An attempt has been made to forecast the monthly rainfall applying Long Short Term Memory for various epoch (s) like 15, 30, 45, 60, 75 and 90 respectively. The factors like Root Mean Square Error (RMSE) and Cosine Similarity (CS) were calculated to judge the quality of forecasting. For various epoch(s) the parameter RMSE were calculated and found as 0.1142, 0.0895, 0.1042, 0.0612, 0.0798 and 0.0673 respectively. Similarly, CS is also calculated for the same epoch(s) and found as 0.9628, 0.9778, 0.9762, 0.9812, 0.9776 and 0.9795 respectively. We found outperform results in 60 epoch(s) for both RMSE and CS. The results exhibited that LSTM networks provide a better result with lower epochs when chosen. These experimental results showed that the LSTM approach gave the best result in predicting rainfall. To improve the result obtained, a hybrid model may be studied in future.

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