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Improving the Accuracy of Rainfall Prediction using Optimized LSTM Model

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Abstract*— Prediction of rainfall is too complex and also it depends on many meteorological factors. India is flourishing country in agriculture. In earlier days, the rainfall is predicted even by common man in the village and they gone for farming. Now a day, due to drastic changes in the climate and weather, accurate prediction of rainfall becomes multifaceted. Information Technology is offering very good techniques for prediction. Deep Learning is one of the latest technology applied in the field of prediction. As the rainfall data is time-series data, Optimized LSTM (OptLSTM) is proposed in this paper. The data is collected from the various districts in Tamil Nadu and used for developing prediction model using LSTM and optimized the hyper parameters with Particle Swarm Optimization (PSO). Series of experiments are conducted to authenticate the proposed model is predicting accurately. The accuracy of the model is evaluated with evaluation measures MSE, RMSE, MAE. The performance of OptLSTM model is compared with other conventional models used for rainfall prediction. Out of those, OptLSTM presents better accuracy.

Keywords: LSTM, Rainfall, PSO, Evaluation Metrics, Prediction.

INTRODUCTION

Rainfall prediction is become complex phenomena due to various meteorological changes in the climate. Accurate rainfall prediction is playing vital role in agricultural sectors. Crop yield is mainly depending on rainfall. Crop planning can be done effectively with the help of accurate prediction of rainfall. Promising results are obtained through techniques like Hidden Markov Model, Auto-encoder, Restricted Boltzmann Machine (RBM), Conditional RBM, Recurrent neural network, Convolution and pooling for time-series data [1]. Table 1 and 2 shows details of various seasons in India and required rain fall, Temperature, etc.

Table 1: Crops and Seasons in India

Seasons	Types of Crops	Duration	Rainfall (in cm)
Kharif	Rice, Maize, Bajra, Ragi, Soybean, Groundnut, Cotton	June - October	100
Rabi	Wheat, Barley, Mustard and Green Peas	November - March	50 - 90
Zaid	Pumpkin, Cucumber, Bitter gourd	March - July	Irrigation

Table 2: Rainfall for Crops

Crop Name	Soil	Rainfall	Temperature
Rice	Deep clayey and loamy soil	150-300	22 -32
Coffee	Well drained, deep friable loamy soil	150-250	15-28
Wheat	Well-drained fertile loamy and clayey loamy	75-100	10-15
Tea	Well drained, deep friable loamy soil	150-300	20-30
Millets	Inferior alluvial or loamy soil	50-100	27-32
Oilseeds	Well drained light sandy loams, red, yellow and black soil	50-75	20-30
Grams	Loamy Soil	40-45	20-25
Cotton	Black soil of Deccan and Malwa Plateau	50-100	21-30
Sugar Cane	Deep rich loamy soil	75-150	21-27

RELATED WORKS

An artificial neural network model is created with feed forward multilayer neural networks for predicting rainfall with time series data collected in Cyprus [2]. Another ANN model is developed using multi-layered feed forward neural networks with error-propagation algorithm to predict rainfall [3]. ARIMA model and LSTM model for forecasting visibility at Hang Nadim Airport, Batam Indonesia was done [4]. Prediction of solar irradiance is done based on weather forecasts and long short-term memory(LSTM) networks [5]. ANNs for predicting the monthly average rainfall in an area of India characterized by monsoon type climate done [6]. The Markov model based forecasting are more suitable for the exponential growth of rainfall. A long term rainfall forecasting model using the integrated wavelet and neuro-fuzzy was proposed by [7]. ConvLSTM is better at capturing the spatiotemporal Correlations and gives accurate prediction [8]. Climate data mining using deep learning techniques proposed by [9]. Artificial Neural Network model was developed to forecasting monthly rainfall one year in advance for locations within the Murray Darling basin [14].

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Using historical data, the ANN model is developed to predict south western monsoon rainfall over India six years in advance [15].

LSTM

In LSTM, the connection between back-nodes and front-nodes is enhanced by forget gate, input gate and output gate. LSTM Network is shown in Figure (1).

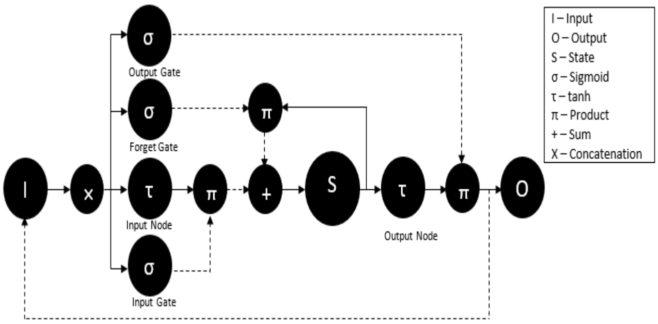

Figure 1: LSTM Networks

The flow of information from input cells and output cells are controlled by the gates. Forget gate determines how long the information should be kept in cell. Forget gate has sigmoid function to transfer selected information.

$$f_t = \sigma(W_{xf}.x_t + W_{hf}.h_{t-1} + b_f) \qquad (1)$$

In Equation (1), x_t is current input, h_{t-1} is previous state and b_f is correction bias of the network. Input gate determines which values used for updating and tanh is used to compute $\tilde{C}_t$. The Equations (2) and (3) are

$$i_t = \sigma(W_{xi}.x_t + W_{hi}.h_{t-1} + b_i) \qquad (2)$$

$$\tilde{C}_t = \tanh(W_{xc}.x_t + W_{hc}.h_{t-1} + b_c) \qquad (3)$$

In Equation (4), the old cell value will be updated.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \qquad (4)$$

Finally, Equation (5) and (6) connects the pre-state with the present temporary state and calculates the output of the model.

$$o_t = \sigma(W_{xo}.x_t + W_{ho}.h_{t-1} + b_o) \qquad (5)$$

$$h_t = o_t * \tanh(C_t) \qquad (6)$$

PARTICLE SWARM OPTIMIZATION (PSO)

The most famous evolutionary computation technique is Particle Swarm Optimization (PSO). It is very useful for non-linear optimization problems [10]. PSO algorithm used to improve the learning strategies of the BP neural network [11]. A learning algorithm based on particle swarm optimization and evolutionary algorithms are proposed [12,13]. The study shown that PSO is efficient to find the optimal number of input, hidden nodes and learning rate on time series prediction problems [16]. As the random initialization of input and output weights of LSTM has significant impact on accurate forecasting. PSO will optimize these weights to improve forecasting accuracy.

```
Particle Swarm Optimization
Input: Initialize PSO with m particles, n iterations per particle.
  for each particle Pari do
    Initialize velocity Vi and position Xi
    Evaluate particle Pari and set Parbest = Xi
  end for
Global_best = min(Particle_best)
for i = 1 to m do
  for j = 1 to n do
    Update the velocity and position of particle Pari
    Evaluate particle Pari
    if f(Xi)<f(Particle_best) then
      Particle_best = Xi
    end if
    if f(Particle_best)<f(Global_best) then
      Global_best = Particle_best
    end if
  end for
end for
return Global_best and the corresponding Xi
```

PROPOSED METHODOLOGY

Figure (2) shows diagram of the proposed methodology. Raw data is pre-processed to impute the missing values and noise. The LSTM Network with Optimization Algorithm, the new model is developed and evaluated with MSE, RMSE and MAE to find the best model which predicts accurately.

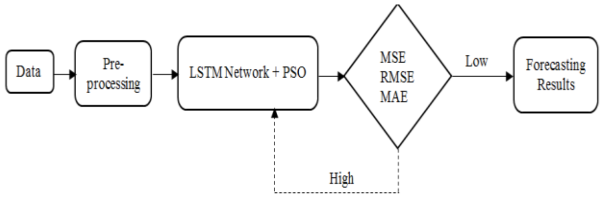

Figure 2: Proposed Methodology

EVALUATION METRICS

Generally, various evaluation metrics are used to measure the performance of the statistical and deep learning models. The developed model evaluated with evaluation measures Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to compare with the normal LSTM model with Optimized LSTM Model. Equations for MSE, RMSE and MAE are as follows.

$$MSE = \frac{1}{n}\sum_{t=0}^{n}(y_t - \hat{y}_t)^2 \qquad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=0}^{n}(y_t - \hat{y}_t)^2} \qquad (8)$$

where y_t is the actual value, $\hat{y}_t$ is the predicted value and n is the total number of observations.

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$$MAE = \frac{1}{n}\sum_{t=0}^{n}|y_t - \tilde{y}_t| \qquad (9)$$

where n is the total number of predictions, y is the predicted value.

RESULT ANALYSIS AND DISCUSSION

The forecasting model for rainfall is developed and trained with the Tamil Nadu rainfall data collected from kaggle. The dataset is imputed with missing values and normalized before using it for training. The rainfall data is split into training data and testing data. The data set contains the rainfall data for each month and four seasons for 115 years (1901-2015). The LSTM model is developed with various hyper parameters and optimized with the help PSO. Batch size is varying from 10 – 50, look back varies from 1 – 10, no. of epochs varies from 10 – 100. With these hyper parameters, the model achieves accuracy of prediction. The developed and trained model is tested with testing data and evaluated with various evaluation measures. The model is tested with monthly data as well as seasonal data (Jan-Feb, Mar-May, Jun-Sep, Oct-Dec). The OptLSTM model works for both monthly data as well as seasonal data. The Figure (3) shows the prediction by normal LSTM model and Figure (4) shows monthly rainfall prediction with PSO.

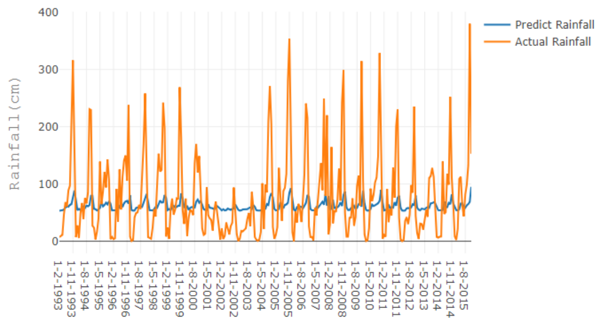

Figure 3: LSTM Model

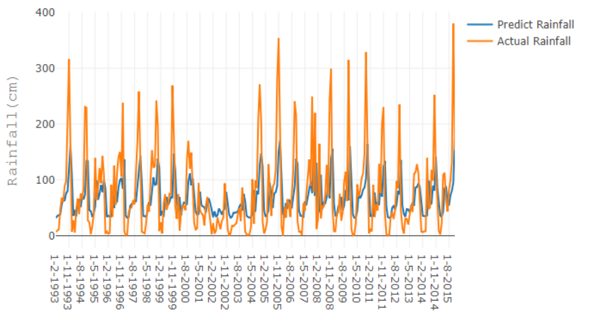

Figure 4: Optimized LSTM Model

The Table 3 shows the comparison between normal LSTM and Optimized LSTM models. The evaluation measure shows the lowest error rate for OptLSTM when compared to normal LSTM. Although, the normal LSTM itself have optimization which gives better accuracy of prediction, the OptLSTM model shows better accuracy than normal LSTM model for training data as well as testing data.

Table 3: Model Comparison

Model	Train			Test		
	MSE	RMSE	MAE	MSE	RMSE	MAE
LSTM	0.025	0.158	0.112	0.028	0.166	0.117
OptLSTM	0.021	0.144	0.102	0.022	0.149	0.103

CONCLUSION

The proposed model attains accurate prediction using Long Short Term Memory Network along with Particle Swarm Optimization. This OptLSTM model is shows the predictions more accurately and efficiently compared with the normal LSTM model. The model works for monthly rainfall data as well as seasonal rainfall data. However, the current model is developed and trained with only data collected from Tamil Nadu State. Hence, further training is required for the model to make efficient prediction for all rainfall data.

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