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Comparative Analysis of Weather Forecasting Using LSTM, BiLSTM, and CLSTM Networks



Abstract: - Weather prediction plays vital role in the evaluation of various processes and phenomenon for the betterment of society. Weather forecasting depends on many parameters hence, it's a multivariable prediction problem. Behavior of data involved in the prediction are in majority of time stochastics hence, conventional mathematical approaches are failed to predict accurate data. Classical computational methods fail in predicting chaotic data due to its limitation to have know-how about behavior of data. Artificial Intelligence and Data Processing techniques is appealing investigators due to its efficiency to predict data based on its learning capability, without any know-how about the behavior of data. In this paper, Artificial Intelligence based approach LSTM, BiLSTM, and CLSTM are used to predict time series weather data prediction. Data considered are Pressure, Humidity, Temperature, and Maximum wind speed as input data. Neural Network based approaches are used to predict Average wind speed based on above inputs. The performance of above Artificial Intelligence approaches is compared to predict time series Average wind speed. MATLAB is used as software tool to implement Artificial Intelligence approaches. It has been observed that CLSTM algorithm outperformed other two algorithms LSTM and BiLSTM algorithm.

Keywords: Weather Forecasting, LSTM, BiLSTM, CLSTM, RMSE, ARIMA

I. INTRODUCTION

Weather forecasting is very important for evaluation of the meteorological parameters [1]. It helps in management of water conditions [2], flood & drought, understanding effect of climate changes [3], marine and agricultural applications and many more [4],[5]. Collections of time series data related to majority of applications are chaotic in nature. Specially, when we have multiple variables are involved as in the case of weather forecasting data are always nonstationary and behave in a state of chaos. In this approach, we have considered physical parameters of Pressure, Humidity, Temperature, and Maximum wind speed to predict Average wind speed from the mention reference website [6]. Forecasting of results dependent of more than one input variable is always a challenge. Even it gets more difficult when there are nonlinear relations among input-output variable and data are non-stationary & chaotic in nature. The problem selected here is having more than one input variable and one output variable and has data which are chaotic in nature. Conventional mathematical formula-based algorithm fails to solve this kind of problems. Hence, Artificial intelligence-based algorithms are employed to forecast data and study the competency of the algorithms. Concise literature review in this filed is carried out in the subsequent section.

II. RELATED WORK

Dynamic and empirical methods are generally used to predict chaotic time series data. Dynamic model is having limitations that, it works based on fixed equation and convergence to fitted model depends on chosen initial conditions methods like ARIMA, ARIMAX, and SARIMAX [7]. Artificial Intelligence (AI) based algorithms have attracted investigators due to its advantages of data prediction without any know how about input output relationship between data. AI based approaches has fast computation power and self-learning capabilities as a result it out performs in continuously changing data series prediction [8],[9]. Selection of algorithm for weather prediction depends on many factors like; behavior of data, continuity, intensity, chaotic or not, univariate or multivariate prediction and many more [10],[11]. Disorganized, heterogeneous, and large digital data are called as big data, in our case we have considered per hour data for a year which results in precisely (24x365=8760) data for each variable under consideration [12]. Fathi et al. (2021) [13] have provided an extensive literature review on the methods for weather forecasting. Comparison between the Autoregressive Integrated Moving Average Model (ARIMA) and Adaptive Network-based Fuzzy Inference system (ANFIS) for weather forecasting, for the physical parameters of relative humidity, air temperature, pressure, and wind direction were carried out. Ramesh Babu et al. concluded that the ARIMA approach gives accurate prediction but it takes more time to predict in

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comparison with ANFIS [14]. Methods for weather forecasting surveyed in the research paper [15] are Random Forest (RF) algorithm, Support Vector Machine (SVM), Neural Network (NN), Naive Bayes, REP tree and bagging algorithm, the nearest neighbors modelling, and Wavelet Artificial Neural Network (Wavelet-ANN) by analyzing more than fifteen papers. Unfortunately, no proper conclusion was derived based on survey done in this research paper as comparison of results are lacking in the literature survey.

This paper focuses on Artificial Intelligence based Neural Network methods of Long Short Term Memory networks (LSTM), Bidirectional Long Short-Term Memory (BiLSTM), and Convolutional Long Short-Term Memory (CLSTM) Networks methods for predicting weather data. Performance of algorithms are compared using Root Mean Squared Error (RMSE) to measures the average difference between values predicted by a model and the actual values and Mean Squared Error (MSE) the average squared difference between the estimated values and the actual value [16].

The present paper is crafted as under: In Section 2, Introduction and concise review of the topic is covered. Algorithm implementation and Results are discussed in Section 3 & 4 consecutively. Conclusion is derived in Section 5.

III. ALGORITHM IMPLEMENTATION

AI based Neural Network approach is classified as a Convolution-based Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). CNNs are mainly used for problems of image recognition while, RNNs for data prediction and analysis. In this paper, we are focuses on various models of RNN based network. LSTM is special type of RNN network called as feedback-based neural network, capable of learning from past data. In this case, the data are traversed only once (i.e., from (input) to (output)) [17]. In order to improve the prediction performance in LSTM network, data are transversed in both directions (i.e., from (input) to (output) and from (output) to (input)) called BiLSTM network. CLSTM is a combination of LSTM and Convolution Neural network. LSTM structure has ability to fit the model and convolution network helps in extracting local and dense features from the data.

1. Data set are taken from website mentioned in reference [4]. Data consist of Temperature, Humidity, Pressure, Maximum windspeed as four inputs and Average windspeed as output.

2. Data is collected every hour for 365 days as a result, total number of data set for each physical variable is (24 hours/day x 365 days = 8760 data/variable)

3. Objective here is to predict one day data i.e. total 24 data for Average windspeed need to be predicted based on four inputs. Hence, actual data available to train the network is (8760-24= 8736) and remaining 24 data will be used for prediction.

4. All Data set will be first Normalized using following formula:

Normalized
$$Var = \frac{(var - minimum(var))}{(var - minimum(var))}$$

- 5. Out of 8760 data set 90% of it will be used for training and 10% for validation.
- 6. Implement Neural Network based on Algorithm: LSTM, BiLSTM, or CLSTM.
- 7. Corresponding to the network set the parameters.
- 8. Apply input and train network for specific number of iterations.
- 9. Predict the output from the trained network.
- 10. Denormalized output using following formula:

*Denormalized var = var * standarddeviation(var) + minimum(var)*

- 11. Plot actual result and predicted value
- 12. Evaluate the Performance of the Neural Networks using performance parameters (1) MSE and (2)

RMSE

13. Derive conclusion

IV. RESULTS

1. LSTM Algorithm and Its Result

The parameters set for algorithms are as under:

Parameters	LSTM	BiLSTM	CLSTM
Number of Inputs	04	04	04
Number of Outputs	01	01	01
Number of Hidden Units	200	200	200
Solver	'adam'	'adam'	'adam'
Maximum epochs	250	250	250
Gradient Threshold	1	1	1
Initial Learning Rate	0.005	0.005	0.005
Learning Rate Schedule	'piecewise'	'piecewise'	'piecewise'
Minimum Batch Size	-	700	700





Fig.1 LSTM algorithm training Progress result





2. BiLSTM Algorithm and Its Result



Fig.4 BiLSTM algorithm training Progress result BiLSTM Training Data, MSE = 0.25439, RMSE = 0.50437, R2 = 0.91867, MAPE = 9.78e-06



Fig.5 BiLSTM algorithm training Data set result



Fig.6 BiLSTM algorithm Testing Data set result

3. CLSTM Algorithm and Its Result



Fig.7 CLSTM algorithm lgraph



Fig.8 CLSTM algorithm training Progress result



Fig.9 CLSTM algorithm training Data set result



Fig.10 CLSTM algorithm Testing Data set result

Algorithm	MSE	RMSE	\mathbf{R}^2
LSTM	0.24059	0.4905	0.50957
BiLSTM	0.18217	0.42681	0.64118
CLSTM	0.025079	0.15836	0.94625

Table 2: Performance of Algorithm on Testing Results

The values used to evaluate the performance measure of the three algorithms are shown in above Table 2. It is well known fact that MSE and RMSE should be as small as possible and R^2 coefficient of correlation should be close to 1 is desirable. Based on above values of parameters conclusion is derived in the following section.

V. CONCLUSION & FUTURE SCOPE

An Objective is to evaluate performance analysis of Artificial Intelligence based algorithms LSTM, BiLSTM, and CLSTM for the problem of Weather Forecasting. The data set for weather forecasting consist of four input and one output. Detailed information regarding parameters set for all three algorithms are mentioned in the Table 1. Figure 1 to 10 shows progress of algorithms, results on training data and testing data. From the Table 2 we can conclude that CLSTM algorithm has lower MSE and RMSE and R² value closer to 1. Hence, we can conclude that CLSTM algorithm outperformed other two algorithm LSTM and BiLSTM algorithms.

In the training of all three algorithms, we have used in built functionality of the network and default parameters of algorithms. We can tune the algorithm parameters by forming objective function of minimizing above errors using any of the Optimization algorithm of Swarm and Artificial Intelligence. This will definitely help us in improvement of results.

Abbreviations and Acronyms

A. Abbreviations	Definition	
AI	Artificial Intelligence	
LSTM	Long Short-Term Memory	
BiLSTM	Bidirectional Long Short-Term Memory	
CLSTM	Contextual LSTM	
REP	Reduced Error Pruning	
MSE	Mean Squared Error	
RMSE	Root Mean Squared Error	
MAPE	Mean absolute percentage error	
Var	Variable	

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