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Hybrid Stacked LSTM Based Classification in Prediction of Weather Forecasting Using Deep Learning

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Article History	***Abstract***
Received: 22 January 2021 Revised: 14 April 2021 Accepted: 19 May 2021	High dimensionality, interactions on numerous distinct spatial and temporal dimensions, and chaotic dynamics are the dominant factors in weather and climate prediction. This research aims at predicting the weather using classification techniques of deep learning. Here we use Hybrid_BiLSTMtechnique which comprises of both LSTM and Bi-LSTM for classification of data. the data has been pre-processed using standard scaling technique before classification. Here, we offer a method for predicting the weather that uses historical data from numerous weather stations to train basic ML models, which can quickly and accurately forecast specific weather conditions for the near future. Keywords: weather forecasting, prediction, deep neural networks, Hybrid LSTM, classification.

1. Introduction:

To comprehend the state of the air for a specific range of location and time, weather determination uses science and current technology. Climate estimates are created by gathering important and quantifiable information about the local environment at a projected location and using climate forecast to extrapolate how the air will change. [1]Deep learning can figure out how to illuminate any situation that requires "thinking" to make sense of it [2]. Weather prediction is the process of predicting future weather patterns using past data that has been gathered.Since it depends on numerous elements, predicting weather conditions is a difficult and intricate procedure. Every few hours, the weather will vary somewhat and occasionally drastically [3].

Proposed contribution is as follows:

- The main objective of research is to enhance network from perturbation effects

- Methodological evaluation of our technique and comparison with several earlier deep learning models in further weather condition prediction.
- Deep learning framework has more advantages in engineering their own features during testing and training the data

2. Related works:

Some of surveys pertaining to weather forecasting are examined in this section. In [4], they conducted a study on big data and its research prospects and examined different DL methods appropriate for processing big data, as well as its difficulties and potential future directions.In [5], the author reviewed a number of weather forecasting methods as well as evaluated their benefits and drawbacks, including statistical, AI, and hybrid models. The research in [6,7] examined wind energy forecasting models and sought to identify trustworthy forecasting models to investigate wind behaviour.In [8-10], they concentrated on hybrid models, ML predictors, and DL predictors for wind speed forecasting. Extreme Learning Machines, SVM, and ANN are three main ML predictors utilised in weather forecasting.The suggested framework offers a detailed categorization of different weather forecasting methods. Survey also presents the most recent weather forecasting models, their difficulties, and their potential applications in the future.

3. System model:

Figure 1 shows the system architecture we suggest. Whereas the suggested General Architecture of the study approach is shown in block diagram figure.1 above. It begins by taking the data from the recorded weather forecast database, and then it uses the Standard Scaler model on the foundation of a knowledge-based neural network to increase feature dimensionality reduction.For this stored data is trained by using Hybrid_BiLSTM to extract feature data to predict the weather.

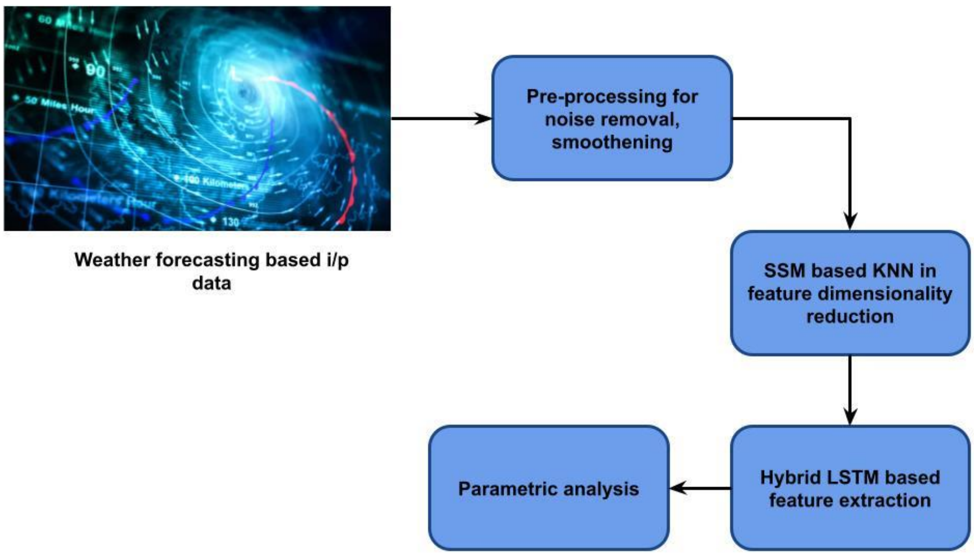


Figure-1 Proposed Architecture

3.1 Hybrid Bi LSTM neural network:

3.1.1 Network Structure:

In this research, a hybrid LSTM_NN structure is suggested to increase precision of weather forecast prediction, as depicted in Figure 2.

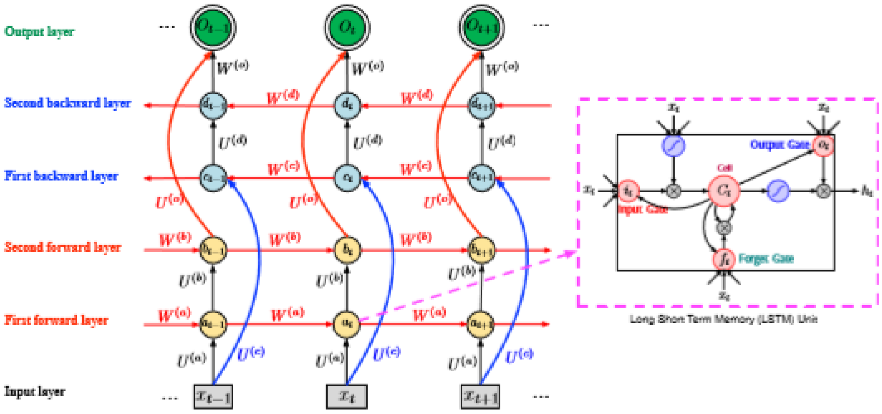


Figure 2. Hybrid_BiLSTM(Long Short–Term Memory (LSTM)-BiLSTM) neural network structure

3.1.2 LSTM Layer:

A group of LSTM units collectively known as the LSTM model make up the LSTM layer. The LSTM model, in contrast to other neural networks, contains three multiplicative units: an input gate, an output gate, and a forget gate. Input gate is used for input, output gate is utilized for output, and forget gate is utilized to decide whether to choose to forget certain past data.Input and output data of LSTM unit are represented by letters t x and ht, respectively. The LSTM unit's processing expressions are as eq. (1):

$$\begin{aligned} f_t &= \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \\ \boldsymbol{i}_t &= \sigma(\boldsymbol{W}_i \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_i) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_i] + b_C) \\ C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \qquad (1) \end{aligned}$$

$$\begin{aligned} o_t &= \sigma(\boldsymbol{W}_o[\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_o) \\ \boldsymbol{h}_t &= o_t * \tanh(C_t) \end{aligned}$$

In order to calculate the output of a forget gate, Equation (1) uses the weighted sum of cell's state at time t, its output at time t 1, and its input at time t as input of the activation function. A ReLU function with parameters is known as the PReLU function. The PReLU function is expressed mathematically as eq. (2):

$$\mathrm{PeLU}(x_i) = \begin{cases} x_i & \text{if } x_i > 0 \\ a_i x_i & \text{otherwise} \end{cases} \qquad (2)$$

If ai = 0, the PReLU function in Equation (3) changes to a ReLU function. tanh function is expressed mathematically as follows.

$$f(x) = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

$$f(x) = \frac{x}{1+|x|} \qquad (3)$$

The logical sigmoid function's initial function, softplus function, is a smooth variant of ReLu function. Softplus function is expressed mathematically as eq. (4).

$$f(x) = \log(1 + e^x) \qquad (4)$$

The linear component primarily performs linear transformation and examines incoming data. It uses a linear weighted sum calculation approach, with the following mathematical eq. (5):

$$Z = W * X + b \qquad (5)$$

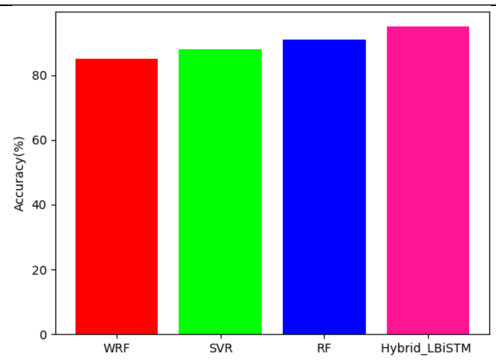
It brings the qualities between - 1 to 1 and keeps a uniform circulation among the loads of the organization. In the yield level , the "Sigmoid" actuation work is utilized. Like " Hyperbolic tangent" it additionally contracts the worth, yet it does it between 0 to 1. The thinking behind this is, if a worth is duplicated by 0, it will be zero and can be disposed of. In the event that a worth is increased by 1, it will stay zero and will be here as it were. Accordingly by utilizing the sigmoid capacity, just the significant and significant worth will be utilized in segmentation.

4. Performance Analysis

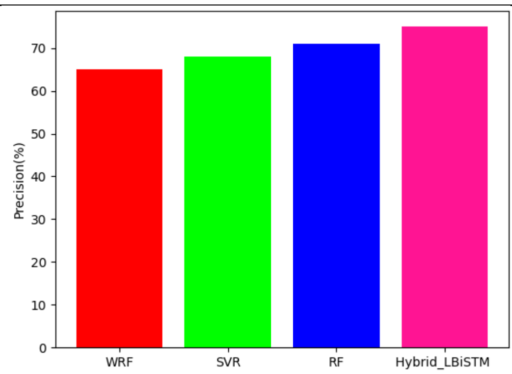
Below is an illustration of the performance analysis of the suggested method. Accuracy, precision, recall, F1 score, and AUC are the factors that should be taken into account while evaluating a parameter. The various performance indicators have been calculated using the output that has been categorised. Clinical datasets are predicted to be used in the evaluation of the proposed methodology. By randomly selecting test data from dataset as result data, performance of the model is examined.

Table 1 Comparison of the Existing and Proposed algorithm of using Weather dataset

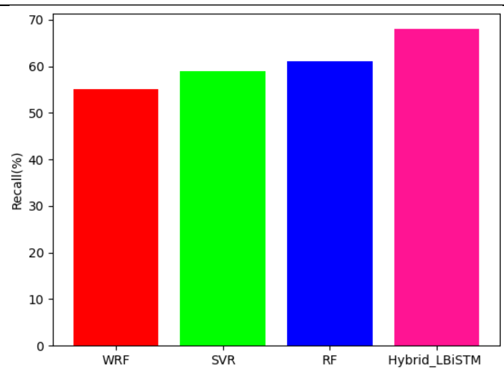
Metrics	WRF (%)	SVR(%)	RF (%)	Hybrid_LBiSTM (%)
Accuracy	85	88	91	95
Precision	65	68	71	75
Recall	55	59	61	68
F1_Score	61	63	66	71
AUC	50	52	55	58



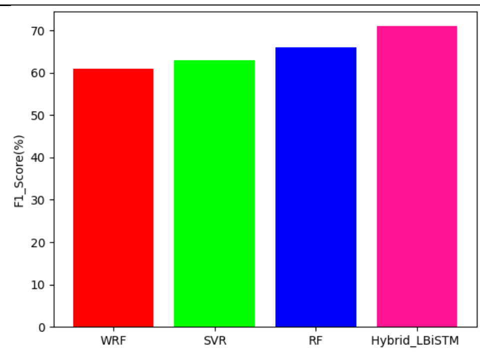
Accuracy



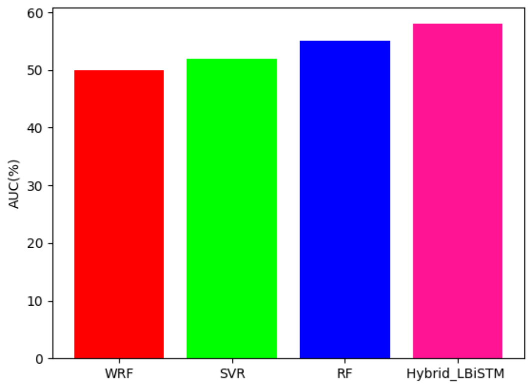
Precision



Recall



F1_Score



AUC

The table.1. shows some of observation of the Weather forecasting dataset, the outcome of the prediction has been estimated from the instances of the Real world IoT data, then rectifying the instances with same observation, then performance measures of various methods of WRF, SVR, RF is compared with proposed methodsProposed_Hybrid_LBiSTM. With a Less %age of current techniques, the Proposed_Hybrid_LBiSTMachieves MSE. Whereas, by having a maximum of training MSE the WRF, SVR, Random forest method has resulted in the worst results. Whereas, by having a maximum of training MAE the WRF, SVR, Random forest method has resulted in the worst results Finally, by acquiring the MAE value of training values of about the Proposed_Hybrid_LBiSTM system performs more effectively of about less1.54% compared to other models.Whereas, by having a maximum of training MAE the WRF, SVR, Random forest method has resulted in the worst results Finally, by acquiring the R-Squared value of training values of about the Proposed_Hybrid_LBiSTM system performs more effectively of about less 1% compared to other modelsWith a Less %age of current techniques, the Proposed_Hybrid_LBiSTM achieves RMSE. Whereas, by having a maximum of training RMSE the WRF, SVR, Random forest method has resulted in the worst results Finally, by acquiring the RMSE value of training values of about the Proposed_Hybrid_LBiSTM system performs more effectively of about less 2% compared to other models.

5. Conclusion:

In this research, the Hybrid_BiLSTM network is formed by LSTM-BiLSTM learning and training model.Because of their special non-linear adaptive processing capability, neural networks have significant advantages in prediction. Traditional neural networks are unable to complete short-term weather forecasting predictions because they depend on preceding several time steps and relationships between time series.Recurrent neural networks are typically used to infer future events from past ones (RNN). Gradient descent is typically employed to assess network performance during the training of neural networks.However, the Back Propagation Through Time (BPTT) training technique is used in conventional RNNs (BPTT). As a result, if the training period is prolonged, the network's residual that must be returned will diminish exponentially, which will cause a gradual renewal of the network's weights.In other words, a memory block is required to store memory because the standard RNN apparent vanishing gradient issue cannot accurately reflect impact of long-term memory in real-world applications.

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