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Weather Forecasting using Hybrid Model

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ABSTRACT

Joining two models help us to get some patterns that would be unreachable to one of both models without the support of another model and this provides good results in time series forecasting. Hybrid models combine the two types of strength of each model. In the Hybrid model an attitude that combines different types of deep neural networks with expectations attitude to model unpredictability. This research presents an execution analysis of hybrid deep learning models and machine learning models compared to autonomous DL models and ML models on various text categorization tasks. The search suggests that hybrid DL and ML models can nicely grab syntactic manifestation of text, extract multiple feature maps, and give better text classification results. The research also shows a better cognition of different hybrid models in the field of text variety.

Keywords: Time Series Forecasting, Deep Learning Model, Machine Learning Model, Hybrid Model, Weather Prediction, Gated Recurrent Unit (GRU), Bidirectional Long Short-Term Memory (BI LSTM)

I. INTRODUCTION

Using Hybrid models, we can take an advantage of both DL and ML models and reduce the disadvantage of both the individual models and provide more accuracy with less computationally extravagant solutions. The betterment in the deep learning model has proven to fulfil excellent results in text category tasks. This achievement is due to DL model potential with less need for the engineered feature to achieve high accuracy. Depending on the task even though their popularity, the models have their powers and drawbacks. In the past, researchers have suggested different hybrid models overcome these drawbacks.

In recent years there are many analyses are done in this field. DL models combine with ML models, this hybrid model is more powerful compared to individuals. In addition, the quest for better text classification precision has led to the preface of hybrid models to design an entire technique with a more powerful architecture for text category tasks. Nowadays, these models are famous in recent years due to their potential to beat autonomous models. Also, this model provides high accuracy and better performance with minimal error.

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II. TIME SERIES FORECASTING

A Time series defines a sequence of time-based orders would be in Seconds, Minutes, Hours, Weeks, Months, and Years. It is monitored from a series of individual-time of successive breaks. It is a flowing chart. To predict the results, the time variable is an autonomous variable and helps the target variable.

For Weather forecasting, Engineering domain, Financial, Signal processing, control systems, and Communication systems the Time series analysis (TSA) is used. Distinct from spatial and other studies TSA involves producing the set of data in certain series. We can forecast the future by using Bi LSTM, GRU, ARIMA, ARMA, CNN, RNN, AR, MA, etc.

III.MODEL DESCRIPTION

A. Gated Recurrent Unit (GRU)

GRU is very equivalent to Long Short Term Memory(LSTM) which is used to control the flow of details. GRU is an upgraded model of standard RNN. GRU is somewhat new as compared to Long Term Short Memory(LSTM). GRU has a simpler structure as they offer some progress over Long Term Short Memory(LSTM). GRUs are quicker to train with compared to Long Term Short Memory(LSTM). LSTM contains three gates so GRU opposed these three gates and GRU contains two gates. One gate is for Reset and the Other is for Update gate.

1) Reset Gate*:* For Short term memory of the network like hidden state(Ht) reset gate is liable. The equation of the rest gate is as below.

$$rt = \text{б}(xt * Ur + Ht - 1 * Wr)$$

Because of sigmoid function value of rt will vary from 0 to 1. For reset gate, Ur and Wr are important matrices.

2) Update Gate: For long-term memory, an updated gate is used and the equation is as below.

$$zt = \text{б}(xt * Uu + Ht - 1 * Wu)$$

Uu and Wu are important matrices in the updated gate.

There is a two steps process to find hidden state Ht in GRU. The first is the Candidate's hidden state and the second one is the Hidden state.

1) Candidate Hidden State:

$$\hat{H}t = \tanh(xt * Ug + (rt \circ Ht - 1) * Wg)$$

The hidden state from the last timestamp t-1 is multiplied by reset gate output rt and the candidate hidden state takes in the input. At last, all data is transferred to the tanh function and the output is the candidate hidden state. The whole data from the last hidden state Ht-1 is being considered when the value of rt is equal to 1. The data from the last hidden state is ignored when the rt value is 0.

2) Hidden *State:*

$$Ht = zt \circ Ht - 1 + (1 - zt) \circ \hat{H}t$$

The first term in the equation will disappear, which means the hidden state does have not more data from the last state while the ut value will be 0. While the second part becomes one which means the hidden state at the recent timestamp will contain the data from the candidate state. While the value of ut is on the second term becomes totally 0 and the recent hidden state will depend on the first term when the data from the hidden state at the last timestamp t-1.

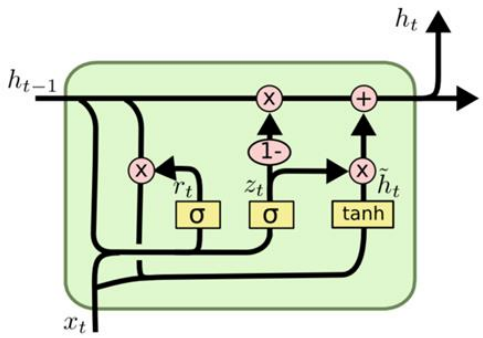

Figure 1: GRU Model

B. **Bidirectional Long Short-Term Memory (Bi LSTM)**

To create a neural network there is a process named Bidirectional long-short term memory (Bi LSTM) that has the series of data in both directions forward (past-future) or backward (future-past). In Bidirectional long-short term memory (Bi LSTM), the input flows in both directions to differentiate Bi LSTM from regular LSTM. For making input flow in either backward direction or forward direction we use standard LSTM. To maintain future and past data we use the input in both directions in bi-directional LSTM.

The concept behind Bi LSTM is total data in the past and future of a particular time in LSTM. At any time, we are able to maintain data from the past and future. Bi LSTM virtually improves the amount of data obtained from the network, enhancing the content obtained to the model using Bidirectional will execute in two methods one from start to end and another from end to start. Disputes this technique from unidirectional that runs backward in LSTM. We hold data from the end. Using two combined hidden states, at any time we can maintain data from start to end.

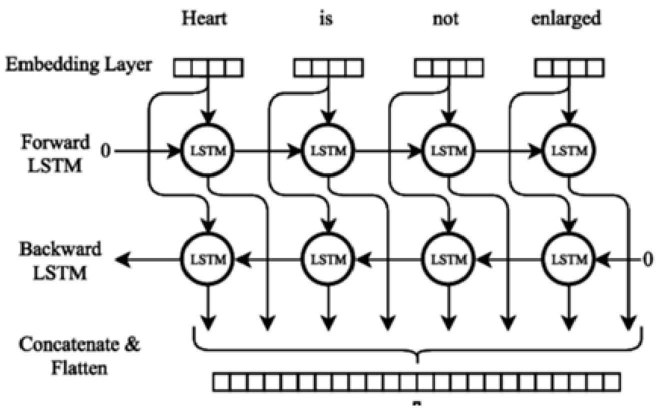

Figure 2: Bi LSTM Model

In the figure, we can see the whole flow of data from backed and forward layers when series to series tasks are needed Bi-LSTM is normally utilized. For forecasting models, text classification, and speech recognition such a type of network is used.

C. **Hybrid Model (Bi LSTM - GRU)**

A gated recurrent unit (GRU) is part of a typical model of RNN that plans to use links through a series of nodes to execute ML tasks connected to memory and clustering. GRU solves the vanishing gradient problem which is a common issue in RNN. The vanilla recurrent neural network suffers when GRUs convey the vanishing gradient problem. To make untrainable the grading contract over time as it back to reproduces and becomes too short to impact learning. RNNs can effectively forget longer series if the layer in a neural net can't learn.

By using the update gate and reset gate GRU solves this problem. These gates determine what data is permitted through to the output and can be trained to maintain data from further back. For making useful forecasts it allows it to pass appropriate data in a chain form.

Bi LSTM is working in both directions, at that time the regular LSTM model is working in single directions. With LSTM and Bi LSTM execution we clearly show that Bi LSTM performance is more than simple LSTM. As small errors affect weather forecast results, so we have to use Bi LSTM to reduce error and improve accuracy.

a) Implementation

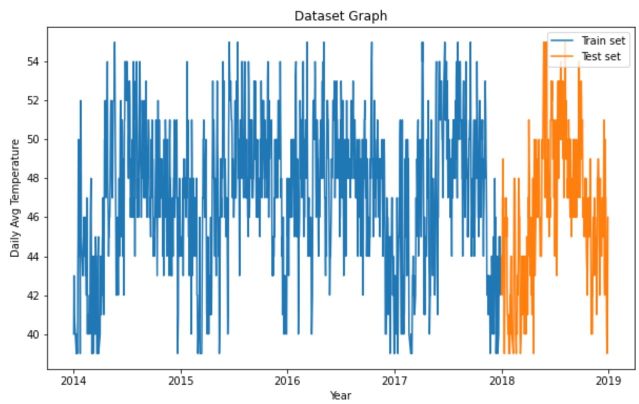

Figure 3: Dataset Graph

The above graph shows four years of weather data. The dataset contains MinTemp, MaxTemp, AvgTemp, Sunrise, and Sunset day-wise. From that data we procedure AvgTemp for the weather forecast.

In the data pre-processing part model first, check a nullable value in the data set after-that min-max scaler is used for rescaling variables into the range 0 to 1. In this hybrid model, the one-one layer is used in each model. Pre-processed data is passed to the hybrid model and the model is trained from this data after that model predicts the data and shows the loss of data stepwise.

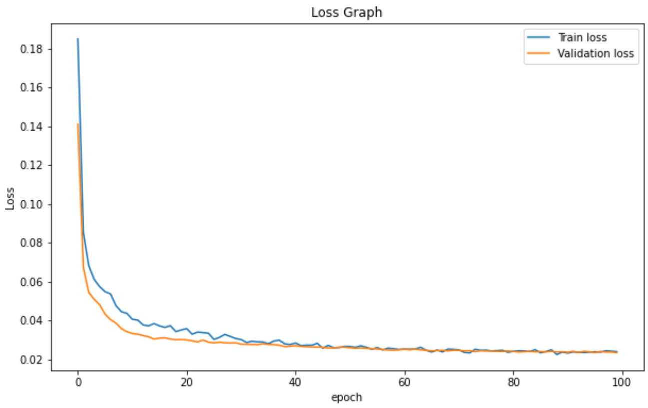

Figure 4: Train loss and Validation Loss Graph

From the graph, we show that every epoch reduces error also train loss decreases, and at one-point train loss and validation loss are the same. The curve of both graphs is similar to each other.

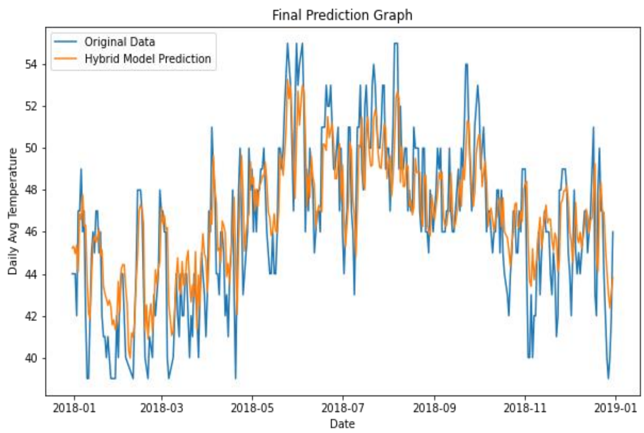

Figure 4: Final Prediction Graph

Fig 4. is a graph of predicted data and actual data. The prediction graph was predicted by the Bi LSTM - GRU Hybrid model. We see that the hybrid model predictions are almost similar to the original data. The hybrid model provides high accuracy in weather forecasting. The model produces less error. The graph show one year temperature forecast. So from this hybrid model, we can predict the future.

Model	MSE	RMSE	MAPE
Bi LSTM	0.1015	0.0461	0.0361
GRU	0.1189	0.0488	0.0393
Hybrid	0.0942	0.0434	0.0349

Table 1: Error Matrix

Error matrix shows that errors are high in the individual model and fewer errors in the hybrid model. The hybrid model works more efficiently than the individual Bi LSTM and GRU models. Bi LSTM has better performance if these operations work correctly. In this research, the Bi LSTM model plays the leading role in better forecasting results.

IV.CONCLUSION

This research aimed to provide a forecast for weather forecasts by deep learning models and machine learning models. We have seen that the hybrid model supplies more precision in long-term forecasting. Compared to individual models error is less. We have seen that two individual models enjoy favourable contrasts. Bi LSTM matches better the stable part of the sequence and GRU is pickier. Due to this, we have to switch to a hybrid model that would only maintain the integrity of the two models.

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