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Hybrid Deep Learning Model (LSTM-CNN) Application for GPS-Based Ionospheric TEC Forecasting

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ABSTRACT:

Deep learning algorithms have shown great promise in forecasting low latitude ionospheric disturbances, such as delays in Global Positioning System (GPS) signals.This letter explores the application of deep learning models, specifically Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and a hybrid model combining LSTM with Convolution Neural Network (CNN), to forecast ionospheric delays for GPS signals. The data used for training and testing the deep learning models is the vertical Total Electron Content (VTEC) time-series data estimated from GPS measurements collected at Bengaluru, Guntur, and Lucknow GPS stations.Among the various deep learning forecasting algorithms for the ionosphere, the LSTM-CNN model stands out with the best performance. It achieves a minimum root-mean-square error (RMSE) of 1.5 Total Electron Content Units (TECUs) and a high degree of accuracy with an R2 value of 0.99. These results demonstrate the effectiveness of the LSTM-CNN model in forecasting ionospheric delays for GPS signals.

Index Terms— Deep learning, forecast, gated recurrent unit (GRU), GPS, hybrid deep learning model [long short-term memory (LSTM)-convolution neural network (CNN)], ionospheric delays, LSTM.

INTRODUCTION

Forecasting the structures and dynamics of Earth's ionosphere plays a crucial role in the effective planning, operation, and management of vital technological systems such as radio detection and ranging (RADAR), communication, and navigation systems [1]. Adverse space weather conditions can significantly affect radio frequency (RF) and global navigation satellite systems (GNSS). When RF and GNSS L-band signals pass through the ionosphere, they experience variations in the index of the ionospheric

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dispersive medium [2-3]. The time delay of these signals is influenced by the total electron content (TEC) in the ionosphere. TEC varies with factors like the time of the day, season, annual changes, and geomagnetic conditions [4]. Ground or space-based GNSS receivers can monitor the behavior of the ionosphere using GNSS signals, providing valuable insights for forecasting ionospheric conditions. Various approaches have been explored for the prediction of ionospheric Total Electron Content (TEC), including neural network (NN), radial basis function (RBF), convolutional neural network (CNN), and long short-term memory (LSTM) models. Sivavaraprasad et al. [5-7] utilized a NN model to forecast VTEC at a low latitude GNSS station. Although they employed ten hidden layers in the network's hidden layer, the NN algorithm faced challenges in capturing long-term data dependencies and experienced slower convergence as the complexity increased. Boulch et al. [8] proposed a convolutional recurrent NN (RNN) to predict ionospheric TEC. RNN was used to capture temporal trends in VTEC values, which were then given to CNN for extracting spatial features from global TEC maps. However, RNN struggled with extracting temporal features from long-term-dependent data due to the problem of vanishing/exploding gradient as the layers increased. To address the limitations of RNN, the LSTM network model was considered more suitable. Srivani et al. [9] implemented LSTM for forecasting VTEC over a low-latitude location and found that nonstationary and nonlinear TEC features were well predicted using the LSTM algorithm. However, LSTM primarily flows temporal information through its layers and may miss the spatial or local hidden features from previous hours' TEC values. To overcome these challenges, a hybrid model called LSTM stacked over CNN (LSTM-CNN) was proposed. The LSTM-CNN model extracts features from bivariate contextual information pairs to obtain forecasts of ionospheric TEC values. By combining LSTM and CNN, the model can effectively capture both local spatial and temporal features from the TEC data sets, leading to improved prediction performance [10].

LSTM-CNN DATA PROCESSING AND HYBRID MODEL

The ionospheric time delay is directly related to the Total Electron Content (TEC). Vertical TEC (VTEC) specifically represents the TEC present in a vertical cross-section area of 1 m^2 of the transmission path and is used to measure the time delay [11]. In this

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research, five solar-terrestrial and geophysical features were considered: day, hour, solar flux (F10.7), geomagnetic activity (AP), and Global Positioning System (GPS) data (TEC). Additionally, sine and cosine components of days and hours were included as features.A total of 70,080 GPS TEC data points were used for training and testing the hybrid LSTM-CNN model. The architecture of the model is shown in Figure 1. Instead of using 1-D convolutions as in previous studies, 2-D convolutions were implemented after concatenating the data on the third axis to enable faster convergence and better learning on the dataset [12]. The model considers VTEC as the key value, and all other features are considered as contextual values. The VTEC dataset is divided into <key, context> pairs, such as <VTEC, F10.7> and <VTEC, AP>, resulting in six features in total, including the GPS data. Each sequence has a bivariate pair of key and context, and at each time step, these six bivariate pairs are fed into the network. For predicting ionospheric TEC, the model uses a sliding window approach with a stride of one-time step, where 14-time steps of prior data are used to make predictions [13].

RESULTS AND DISCUSSION

The dataset used for training and evaluating the forecasting Total Electron Content (TEC) models consists of hourly data points of GPS measured VTEC time-series data taken over Bengaluru station, located at geographical latitude 12.97°N and geographical longitude 77.59°E. The data spans eight years, from 2009 to 2016. To train the deep learning models, the first six years of data (2009 to 2014) were used as the training set. The data from the year 2015 served as the cross-validation set, while the data from the year 2016 served as the testing set for evaluating the performance of the forecasting TEC models [14]. The dataset covers the 24th solar cycle and includes data from two solar phases. The period of 2012 was considered the ascending solar phase (ASP), while 2014 was the solar maximum. The maximum VTEC values were observed during the 2014 period, as shown in Figure 2. This information allows the models to be trained and evaluated on data from different solar phases, providing a comprehensive assessment of their forecasting capabilities [15].

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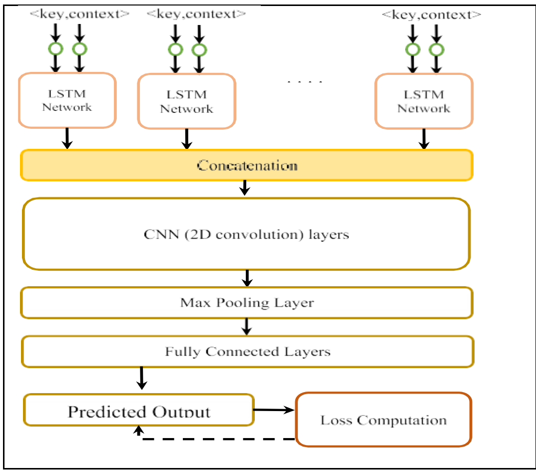

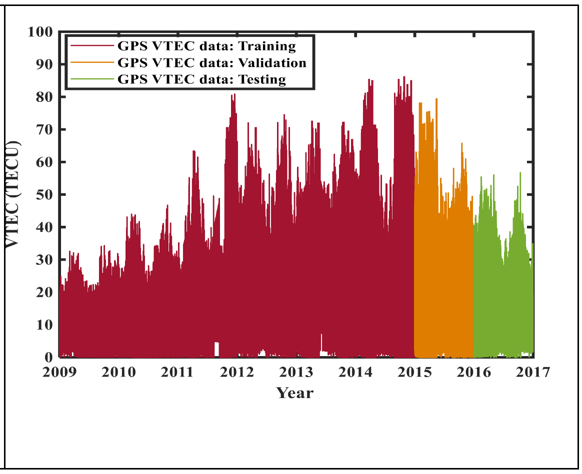

Figure 1 illustrates the architecture of the proposed hybrid deep learning model that combines CNN and LSTM

Figure 2 shows the splitting of the GPS-VTEC data for the LSTM-CNN hybrid deep learning model. The statistics over the last eight years are from the 24th solar cycle (2009–2016).

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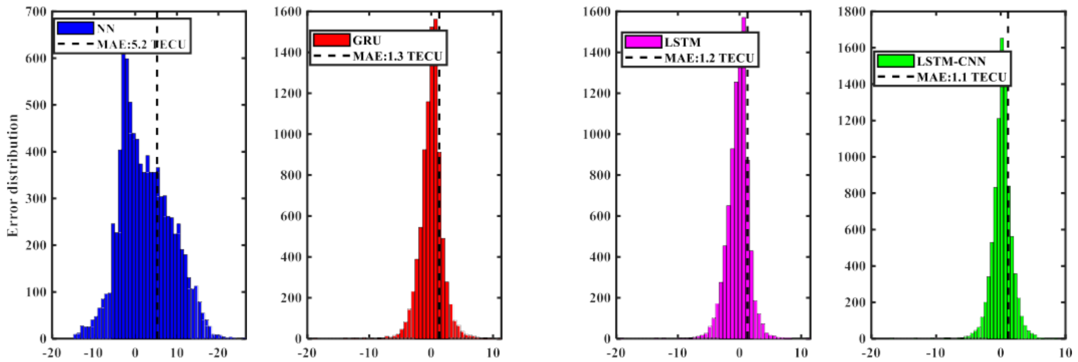

Figure 3 Deep learning algorithm forecast error distribution during testing period, 2016.

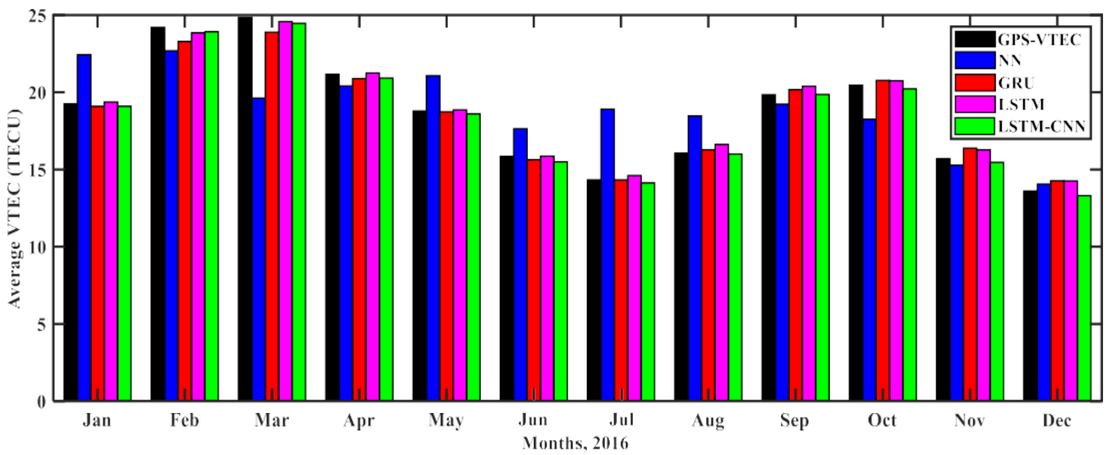

Fig. 4. Comparison of monthly averaged VTEC values estimated from GPS measurements with forecast VTEC values from deep learning models.

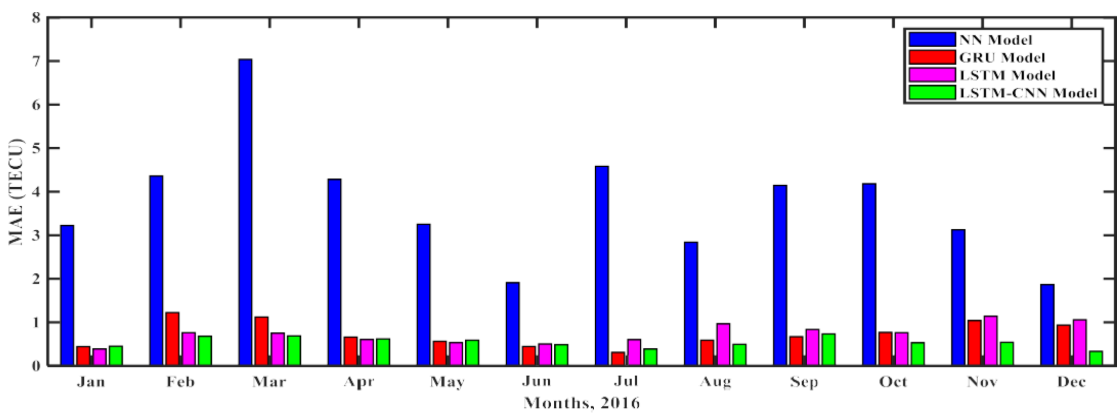

Figure 5 illustrates a performance analysis of the forecasting outcomes attained by various deep learning models in 2016.

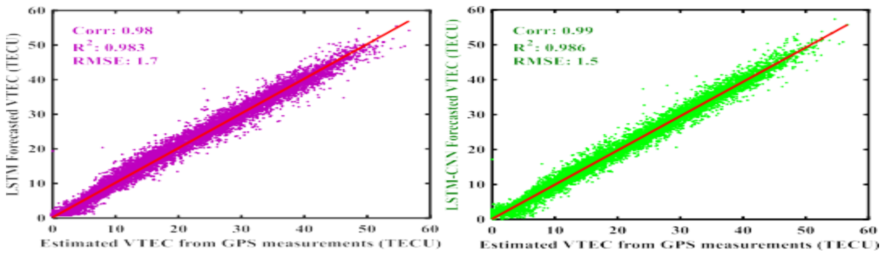

Figure 7 shows the leftovers from deep learning models used to predict seasonal GPS-VTEC variations in 2016.

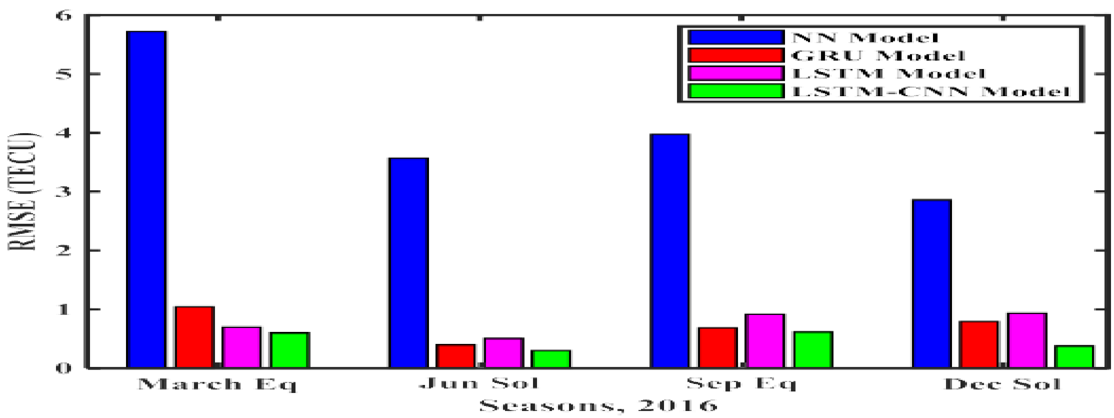

Figure 8 shows the correlation between the proposed LSTM-CNN hybrid deep learning model and the proposed NN, deep learning models (GRU, LSTM), and estimated VTEC from GPS measurements across the testing period in 2016.

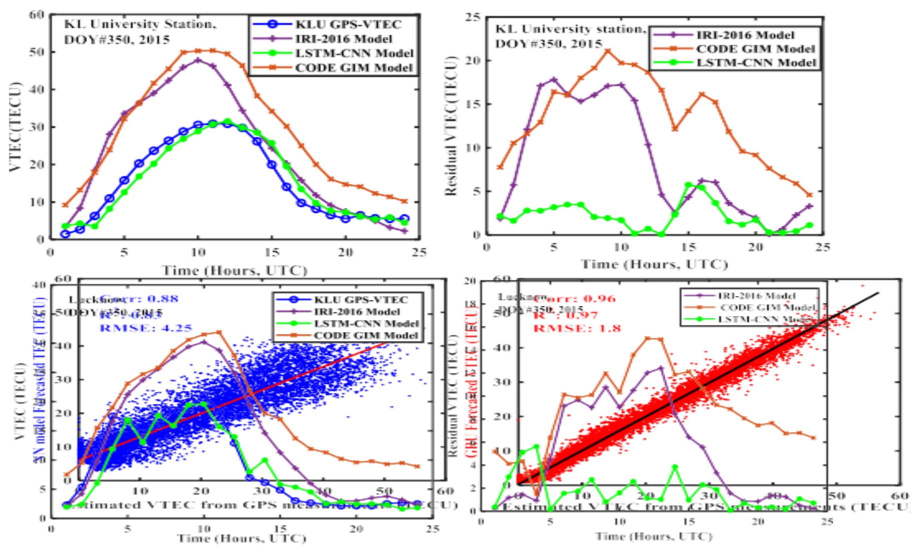

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Figure 9 shows a comparison of the LSTM-CNN forecasting results with those from CODE GIM and IRI-2016 models, two other global models.

CONCLUSION

The evaluation is conducted for one year (2016) with a training period of VTEC data covering six years (2009–2014) and a validation period of one year (2015).The experimental performance of the LSTM-CNN model is assessed by comparing it with other conventional models using error measurement metrics during the test period (2016). The monthly averaged VTEC values estimated from GPS measurements are compared with forecast VTEC values from the deep learning models. The comparison results indicate that the deep learning models have an error of less than 1.5 Total Electron Content Units (TECU).Notably, the LSTM-CNN model shows relatively lower Mean Absolute Error (MAE) for the months of February to April, August, and October to December in 2016 when compared to the other models. On the other hand, the NN model exhibits MAE values ranging from 2 to 7 TECU in estimating the monthly averages of GPS-VTEC values. However, the NN model does capture the seasonal variations of VTEC.

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