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Research Article

Ionosphere Model Development using Long Short Term Neural Netwrok

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ABSTRACT

The ionosphere plays a critical role in global communication systems, yet its complex and dynam-ic nature poses challenges for accurate modeling and prediction. This paper presents the develop-ment of an advanced ionosphere model using the Long Short-Term Memory (LSTM) method, a specialized type of recurrent neural network designed for sequence prediction and temporal data analysis. The proposed model leverages historical ionospheric data to capture temporal dependen-cies and predict ionospheric parameters with high accuracy. Comprehensive experiments were conducted using real-world datasets, demonstrating the model's ability to outperform traditional statistical and machine learning approaches in terms of predictive performance and robustness. Key contributions include the implementation of a data preprocessing pipeline to address noise and anomalies, the optimization of LSTM hyperparameters for geophysical data, and a compara-tive analysis with existing models. The results highlight the LSTM method's potential to enhance ionospheric prediction, offering valuable insights for satellite communication, navigation systems, and space weather forecasting. This study underscores the viability of deep learning techniques for advancing ionosphere research and lays the groundwork for future innovations in space sci-ence applications.

Keywords- *Ionosphere Model Development, Artificial Neural Network, LSTM*

I. INTRODUCTION

The ionosphere is a vital and dynamic component of Earth's atmosphere, situated approximately 80 to 1000 kilometers above the surface. This crucial layer plays a key role in supporting life by expanding and contracting based on the solar energy it absorbs [5].Comprising three primary sub-layers—D, E, and F—it serves as a shield against harmful ultraviolet radiation from the sun while significantly influencing global communication and navigation systems. Understanding the ionosphere's structure is essential for improving the accuracy of positioning, timing, and sensitive communication technologies. However, variations in ionospheric electron density pose challenges for radio signals, often causing delays and distortions during their transmission between satellites and receivers. These fluctuations, driven by the dy-namic ionization process, can lead to substantial positioning errors, underscoring the need for precise ionospheric modeling and analysis.

A. Total Electron Content

The ionosphere contains a vast number of electrons formed through the process of ionization. This ionization enables various applications that rely on the presence of these electrons at different times [21] The Total Electron Content (TEC) refers to the total number of electrons along the path between a radio transmitter and receiver. These electrons in the ionosphere's layers significantly influence radio wave propaga-tion. Monitoring TEC is crucial for ground-to-satellite communication, satellite navi-gation, and understanding potential impacts of space weather [20] Predicting TEC can help address multiple challenges. Various global methods for TEC calculation have been developed and tested, such as the Klobuchar model for GPS, the Interna-tional Reference Ionosphere (IRI) model for ionospheric parameters, the NeQuick model for estimating electron density, and the NeQuick-G model implemented in the Galileo system for single-frequency users [31].

$I = (40.3/f2) * TEC \quad (1)$

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Equation (1) gives the I, the Ionospheric delay (m) at frequency f (Hz) and TEC(el/m2) is the total electron count. This formula highlights the dependency of ionospheric delay on both frequency and electron content

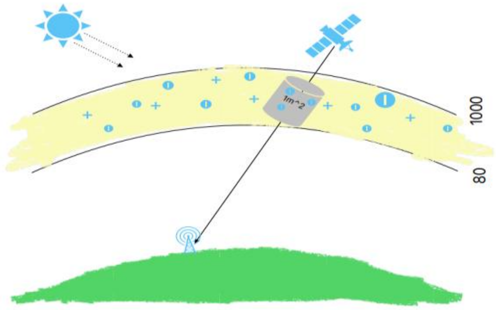

Fig:1 Slant TEC (STEC) from a satellite to a receiver

B. Electron Density

Developing an ionosphere model necessitates a detailed understanding of electron density, which is influenced by several factors such as electron and ion temperatures, ionospheric composition, and dynamic behaviors. These characteristics vary signifi-cantly based on latitude, altitude, longitude, time of day, solar activity cycles, and geomagnetic conditions. Notably, ionization variations are more pronounced near the equator and at the polar regions, while mid-latitude areas experience relatively mod-erate changes [22].Various approaches have been utilized to measure electron densi-ty, including physics-based simulations that rely on numerical methods to model the complex interactions within ionospheric plasma. These simulations, however, require advanced computational resources and are often impractical for operational applica-tions due to their high cost. Alternatively, experimental modeling offers a statistical approach to predict electron density by analyzing observed relationships between input and output variables, providing a more feasible solution for certain scenarios [22]

C. Ionosphere Tomography

Tomography of the Ionosphere is the technique which can compute electron density. Tomography is separating concluded the use of any kind of fundamental wave. The method is used in radiology, archaeology, natural science [10]. 3D Computed To-mography (CT) is a nondestructive scanning procedure that allows to view and ex-amine the peripheral and inside associations of an object in 3D space. Ionosphere tomography is a specific ill posed problem which does not fulfill necessities of well posed problem also which is having smaller number of observation in the edge of the lower latitudes of Indian region. To measure electron density Total Electron Count (TEC) function is used which detect amount of free electrons per square meter in the ray pathway of regional navigation satellite system [3]. As this is an ill posed problem there is no detailed modernization of ionospheric electron density distribution. Com-puterized Ionospheric tomography concerns with voxels which is imaging by section. This inverted ionospheric electron density voxels attained deprived of experimental data efficiently depends on initial value.

II. LSTM

Long Short-Term Memory (LSTM) networks have become a cornerstone in deep learning due to their exceptional ability to capture long-term dependencies in sequen-tial data. Unlike traditional neural networks, LSTMs are equipped with memory cells that enable them to retain information over extended periods, making them particu-larly effective for tasks involving time-series analysis, natural language processing, and speech recognition. Their ability to mitigate the vanishing gradient problem in-herent in standard Recurrent Neural Networks (RNNs) allows them to model complex temporal dynamics in data. This unique characteristic has made LSTMs indispensa-ble in a wide range of applications, including machine translation, sentiment analysis, and predictive analytics, positioning them as a critical tool for advancing research in fields requiring sequential data processing.

III. RELATED WORK

LSTM-NN model was developed that enhances the prediction of ionospheric param-eters by incorporating solar and magnetic indices[29]. During storm conditions, the TEC RMSE for the first and second hour is 1.27 and 2.20 TECU, respectively, while during quiet conditions, it is 0.86 and 1.51 TECU.Bi-LSTM model was

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introduced that effectively utilizes both past and future data to improve TEC predictions and captures the cyclic behavior of TEC[16]. Piecewise LSTM model was proposed, which differs from regular LSTM models by ensuring that forecast error remains con-stant regardless of the number of forecast hours, with an error of less than 3 TECU[22]. RNN model was applied for 24-hour TEC forecasting at the Beijing sta-tion, reducing the RMSE by 0.36 to 0.47 TECU[15]. The EEMD-LSTM model, intro-duced which addresses the dynamic nature of ionospheric data by overcoming the limitations of traditional methods. This model achieved an RMSE of 0.6904 and an R2 value of 0.9969[39]. LSTM-CNN model, which integrates spatial features, over-coming the LSTM's limitation of focusing solely on temporal data[4]. This model outperformed others with an RMSE of 1.5 TECU and an R2 of 0.929.ICEEMDAN-LSTM model was utilized , which applies the ICEEMDAN decomposition to expand time-series data into multi-dimensional space and preserves long-term data infor-mation using LSTM, achieving an RMSE of 0.40 MHz and an R2 of 0.98 across four stations in 2014[11]. Finally, Seq2Seq-LSTM-Attention model presented, which fo-cuses on the significance of different parts of the sequence to improve prediction accuracy, outperforming LSTM, Bi-LSTM, and Seq2Seq-CNN-Attention models.

IV. CHALLENGES AND OPPORTUNITIES

In recent decades, the development of ionosphere models has gained significant at-tention due to the critical importance of reconstructing ionospheric electron density for applications in navigation, positioning, and radio communication systems. While datasets from various locations have been utilized to model electron density, the problem remains complex and under-constrained, necessitating further research and the exploration of innovative methodologies. Historically, the calculation of Total Electron Content (TEC) has relied heavily on ionosondes, which measure ionospheric reflections at different wavelengths to monitor the lower ionospheric layers. Despite these advancements, more precise and comprehensive techniques are required to address the challenges posed by this intricate problem

A.Dataset

Various datasets have been employed in developing diverse models, including the U.S.-based GPS, which serves as the backbone for global navigation satellite systems (GNSS) and provides worldwide coverage. In addition to GPS, other satellite systems such as GLONASS (Russia), Galileo (European Union), BeiDou (China), and QZSS (Japan) have been established to deliver both global and regional navigation capabili-ties. For the Indian region, GPS satellites have been used extensively under all climat-ic conditions. To enhance accuracy, the Indian Space Research Organization (ISRO), in collaboration with the Airports Authority of India (AAI), has developed the 'GPS Aided GEO Augmented Navigation' (GAGAN) system. India also possesses its own independent satellite navigation system, the Indian Regional Navigation Satellite System (IRNSS), designed to provide position, velocity, and timing services across the Indian region. This system offers two types of services: the Standard Positioning Ser-vice (SPS) for civilian applications and the Restricted Service (RS) for strategic use. Beyond navigation, signals from these systems are utilized for various other applica-tions, depending on the quality and nature of the data they provide[14].

V. EXISTING MODEL PROBLEM SURVEY

According to various studies, numerous ionospheric models have been developed to predict total electron density with both spatial and temporal objectives. However, these models predominantly rely on GPS satellite data and are often designed for specific time durations. The ionosphere exhibits a range of atmospheric attributes that directly or indirectly influence electron density, yet many existing models ac-count for only a limited set of parameters. Variations in the path and speed of radio waves traveling through the ionosphere significantly impact the accuracy of satellite navigation systems such as GPS and GNSS. Fluctuations in the ionospheric Total Electron Content (TEC) can introduce substantial errors in position calculations. Therefore, there is a critical need to develop ionospheric models tailored to the lati-tudes of the Indian region, considering varying time frames, to improve the prediction of electron density.

VI. PROPOSED WORK

The development of an ionosphere model using Long Short-Term Memory (LSTM) networks involves the following steps to accurately predict ionospheric behavior over time: First step is Data Collection and Preprocessing: Collect ionospheric data, includ-ing parameters such as Total Electron Content (TEC), solar activity, and geomagnetic indices, over a specific time period. Perform data cleaning to remove any missing values or outliers. Normalize the data using techniques like Min-Max scaling to en-sure all input features are

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on the same scale, improving the efficiency and accuracy of the LSTM model. Next step is Feature Selection: Identify the relevant features that influence ionospheric variations, such as solar flux, geomagnetic disturbances, and temporal variables like time of day and seasonality.Perform feature engineering, if necessary, to create new features that can help improve model performance (e.g., rolling averages or lag features to capture temporal dependencies).
The dataset is split into training (70%), validation (15%), and test (15%) sets, ensuring chronological order to prevent data leakage. A multi-layer LSTM network is designed, with LSTM layers followed by dense layers for output prediction, and dropout layers to prevent overfitting. The model is trained using Mean Squared Error (MSE) as the loss function and the Adam optimizer, with performance monitored on the validation set to tune hyperparameters like learning rate and batch size. After training, the mod-el is evaluated on the test set using metrics like RMSE and R-squared, followed by error analysis to refine predictions. Model refinement may involve adjusting hyperpa-rameters, enhancing features, or exploring advanced techniques like bidirectional or stacked LSTMs. Once optimized, the model is deployed for real-time ionospheric forecasting or research, with continuous updates as new data becomes available. This approach leverages LSTM capabilities to model temporal dependencies in ionospher-ic data, improving prediction accuracy and understanding of ionospheric conditions.

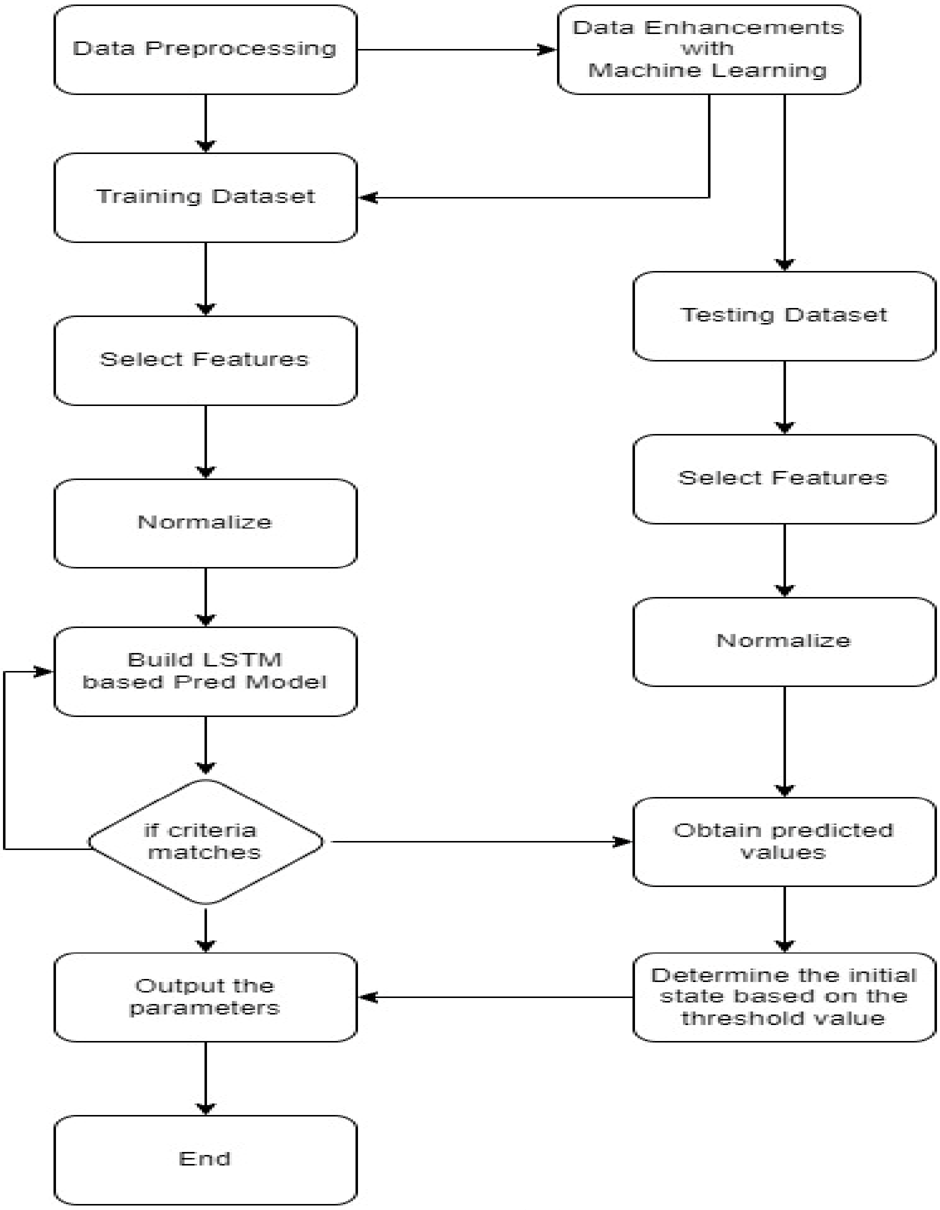

Fig:2 Proposed Flow

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VII. RESULTS

The development of ionosphere models using Long Short-Term Memory (LSTM) networks has shown significant potential in enhancing the accuracy of ionospheric predictions. LSTMs, with their ability to capture long-term dependencies in sequential data, offer a powerful tool for modeling the complex temporal dynamics of iono-spheric parameters, such as Total Electron Content (TEC) and electron density. By training LSTM models on large datasets from GNSS receivers and satellite measure-ments, these models are capable of delivering more precise predictions compared to traditional methods. The ability of LSTMs to handle nonlinearities and the intricacies of ionospheric behavior leads to better forecasting of ionospheric conditions, which is crucial for applications such as navigation, communication, and weather forecasting. Furthermore, incorporating advanced LSTM architectures, such as stacked or bidirec-tional layers, can further improve performance by capturing even more complex relationships within the data. These advancements pave the way for more reliable and accurate ionospheric models, contributing to enhanced understanding and prac-tical applications in the field. Total mean square error on sample dataset for 3 hours is 10.12 which is significantly lower than other models like regression and basic AI models where MSE is 30.98 for the same dataset.

```
In [4]: TEC.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1198 entries, 0 to 1197
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   TOWC (s)         1198 non-null   int64
 1   Hour             1198 non-null   int64
 2   Minute           1198 non-null   int64
 3   Seconds          1198 non-null   int64
 4   UTC TIME         1198 non-null   object
 5   IST Time         1198 non-null   object
 6   Iono Delay-2 (m) 1198 non-null   float64
 7   Correct TEC      1198 non-null   int64
dtypes: float64(1), int64(5), object(2)
memory usage: 75.0+ KB
```

Fig:3 Dataset overview

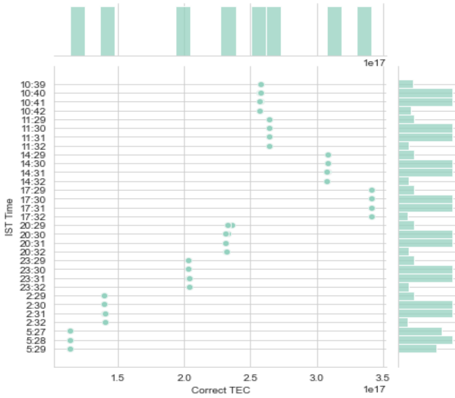

Fig:4 Time vs TEC

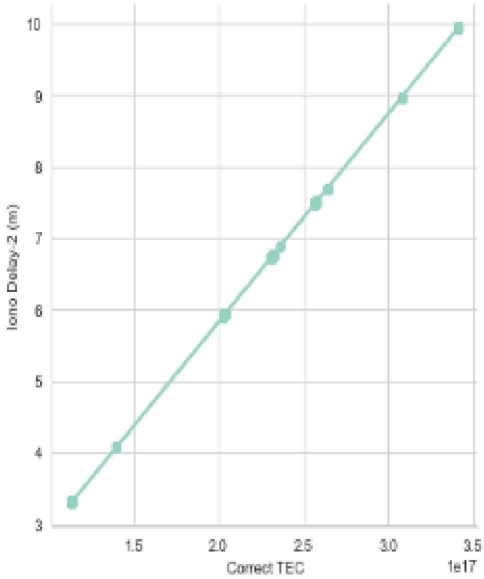

Fig:5 Iono Delay vs TEC

VIII. CONCLUSION

Despite the development and widespread use of various methods over the years, a key challenge remains that the problem is still ill-posed and ill-conditioned. In iono-spheric models, achieving the right balance between resolution and accuracy is essen-tial. The size of the model parameters should be carefully selected based on the dis-tribution of GNSS receivers and the correspondi ng rays they detect. The Total Elec-tron Content (TEC) of the ionosphere plays a vital role in understanding its structure, as well as ensuring precise alignment, navigation, and electromagnetic wave propaga-tion. A modified LSTM model has demonstrated the ability to produce more accu-rate and reliable results for the Indian region, using a sample dataset spanning three hours. This advancement has the potential to significantly improve research in iono-spheric electron density applications, including weather prediction and navigation systems for the Indian region.

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