AI-Driven TEC Prediction Using Spatial Weather Insights: A Web-Based Solution

Ananya Srivastava
Department of Computer Science
KIET Group of Institutions Ghaziabad, India
ananya.2125cs1114@kiet.edu

Aryan Kaushik
Department of Computer Science
KIET Group of Institutions Ghaziabad, India
aryan.2125cs1203@kiet.edu

Manas Rai
Department of Computer Science
KIET Group of Institutions Ghaziabad, India
manas.2125cs1074@kiet.edu

Harsh Khatter
Department of Computer Science & CSIT
KIET Group of Institutions Ghaziabad, India
harsh.khatter@kiet.edu

***Abstract*—Total Electron Content (TEC) is a vital parameter for the analysis of the ionosphere, which has major implications for satellite communications, positioning, and space weather. This research paper describes an AI-based predictive model that uses spatial weather information for the reliable prediction of TEC changes. This paper details a novel system, which combines state-of-the-art machine learning approaches with a web-based interface for users to visualize, analyze, and interact with instantaneous TEC predictions. Providing a dynamic and scalable solution, this study aims to overcome the limitations of traditional Indian methodologies, hence increasing the accuracy and accessibility of prediction. Above all, this study has transformative potential in connecting theoretical innovations with practical applications, establishing a precedent in ionospheric research while also inspiring innovations in vital domains such as the aerospace sector, telecommunications, and disaster management.**

***Keywords*—Total Electron Content (TEC), Spatial Weather Data, TEC Prediction, Ionospheric Variations, Space Weather Forecasting**

I. Introduction

Total Electron Content (TEC) is the parameter that reflects Earth's ionosphere and indicates the total number of free electrons in a certain column in the atmosphere [1]. It acts as a key variable to estimate data in satellite communication, navigation systems, or space weather forecasting. Variations in TEC that can be possibly attributed to solar activity and geomagnetic changes will greatly influence the accuracy of satellite navigation systems and radio signals [2][3]. Hence, the predictions of TEC in space weather become essential for reducing such effects.

This study proposes an AI-based TEC prediction method by leveraging spatial weather data to build a very accurate and dynamic model.

In contrast with traditional statistical approaches evidenced in prior literature [4][5], the method embodies advanced ML algorithms with holistic datasets. Moreover, the first deficiency was compensated by the use of our web-based solution, which provides an easy-to-use web- based interface [17] for researchers and professionals to interact with real-time TEC prediction via visualization and actionable insights.

This particular research highlights the constraints of conventional Indian techniques that are heavily dependent on a limited amount of real data projects into the future from the perspective of AI capabilities [6] to the current day of real-world applications it is made easier and better through the accessible efficient and accurate estimations of TEC on a much wider scale in important areas like aerospace defense and telecommunications.

II. LITERATURE REVIEW

Current research in TEC predictions has met considerable focus owing to its dependency on satellite communication and navigation. ARIMA-type models [7] have been used traditionally to predict TEC values, but are limited in our dealings with complex patterns during periods of geomagnetic disturbances. The LSTM [14] networks have been proven effective in earlier studies to tackle the vanishing gradient problem and boosting the accuracy of predictions for the TEC, especially during quiet and stormy space weather conditions. Another approach, the NARX neural network [8], adds time parameters along with TEC data, which were able to achieve great accuracy com- pared to those TEC predictions made during different solar activity. GPS-based TEC measurements have also provided insights from techniques like Faraday rotation and very robust preprocessing methods like cycle slip correction for data consistency [9]. Building on this, the present research proposes an innovative forecasting of TEC variation using hybrid algorithms of machine learning namely, Neural Prophet [10] and Linear Regression [14]. The model exploits the integrated space-weather data alongside time-series analysis to provide high accuracy and reliability with a user-friendly interface declared through a web application [15]. This is one means of addressing the limits of traditional modelling, suggesting a way forward in a more scalable manner.

A. TEC Measurements and Data Sources

The use of GPS data for real-time Total Electron Content (TEC) measurements was explored through Faraday rotation effects, providing high-frequency TEC readings every 30 seconds within a 1000 km radius [16]. Despite cycle slip issues, this data has proven invaluable for ionospheric research and model training. Similarly, a long-term analysis of GNSS and ionosonde data, spanning 22 and 62 years respectively, estimated once-in-100-year TEC events reaching 150–190 TECU [16]. These datasets provide a solid foundation for training and validating machine learning models, ensuring they generalize well across varying solar and geomagnetic conditions.

B. Traditional Statistical and Machine Learning Approaches

Early statistical models such as ARIMA were employed for TEC time series prediction, but their linearity restricted accuracy during geomagnetic disturbances. It was shown that Long Short-Term Memory (LSTM) networks performed better than ARIMA, with a prediction accuracy of 1.43 TECU, particularly during solar storms. This emphasizes the power of recurrent neural networks in dealing with irregular time series data, supporting the applicability of deep learning for space weather forecasting. A real-time TEC forecasting adaptive regression model was introduced that updated itself dynamically with new data, minimizing ionospheric delay error in single- frequency GPS receivers [17]. Their adaptive solution improved navigation accuracy, with the potential of continuously learning systems.

C. Advanced Neural Networks and Ensemble Models

A TEC prediction mode based on Random Forest and deep learning algorithms was formulated using observational IRI data [18]. Their findings indicated that accuracy could be enhanced with more leaf nodes, albeit at a computational expense. The authors also constructed a web application in Flask, providing access and scalability to the model, consistent with contemporary, cloud-integrated forecasting systems. Also, a NARX neural network was suggested, having a 43.5% improvement in accuracy during high solar activity years [19]. The use of solar and geomagnetic indices as external variables supports our research aim of combining multiple space weather parameters to improve predictability.

D. Spatial and Regional Prediction Models

Principal Component Analysis (PCA) and Kriging spatial interpolation was employed in regional TEC mapping with an accuracy of 12.76% Relative Root Mean Square Error (RRMSE) [20]. This particular previous work highlights the significance of spatial characteristics, proposing that the use of temporal AI models in combination with spatial interpolation has the ability to improve regional accuracy. For example, TEC increased during positive storms and dropped markedly during negative ones during geomagnetic storms, correlating TEC variability with solar cycles and geomagnetic indices such as DST. Such findings inform the choice of appropriate input features for machine learning algorithms.

E. Emerging Techniques and Future Directions

In addition to traditional ML models, scientists have begun investigating hybrid and generative models for predicting TEC. Generative Adversarial Networks (GANs), hybrid LSTM models, and adaptive neuro-fuzzy systems have demonstrated potential for capturing sudden ionospheric changes. Although not yet in general use, these methods hold future promise for improved long-term accuracy and coping with extreme space weather events [21].

III. TOOLS AND TECHNOLOGY

The integration of AI-based TEC prediction systems into development and deployment required the merging of heterogenous tools and technologies. The subsequent section describes the tools used and the purpose of the project.

A. Development Environment

Visual Studio Code (VS Code): VS Code is an IDE that was employed throughout the entire project. This fact proved very useful for managing the workflow very conveniently, with the support for extensions and other features, i.e. debugging facilities, and a terminal built in.

Python: Being one of the most widely used general-purpose programming languages, Python was used because of its rich libraries for machine learning and data analysis. It allowed rapid prototyping and deployment of the TEC predictive model.

Virtual Environment: To avoid interdependence, a virtual environment was created to provide isolation and control over project-specific libraries. This presented consistency across different systems and avoided conflict with the global installations.

B. Data Handling and Preprocessing

Pandas: Pandas was used for preprocessing and manipulating the big TEC datasets. These include parts related to data clean-up, dealing with missing values, and a certain structure of the data.

NumPy: NumPy enabled numerical computations and matrix operations required for data preparation. The ability to operate on large data sizes further made the data processing bottom-line easy.

C. Data Visualization

Matplotlib: Plots like line graphs, scatter plots, and histograms were generated using Matplotlib. The plots revealed the trends and patterns hidden in spatial weather data.

Seaborn: Seaborn enriched visualizations with beautiful and pertinent graphs. It was used to give further emphasis on relationships and correlations embedded in the dataset.

D. ML Framework

TensorFlow: TensorFlow was at the heart of model building processes. Its high level of support for deep learning frame- works provided the opportunity to apply sophisticated neural networks to make accurate predictions of TEC variation.

TensorFlow-add-ons: TensorFlow-addons provided special features to include and implement custom loss functions and evaluation metrics, which maximized the model's predictive performance.

Scikit-learn: Scikit-learn is a library used for auxiliary tasks in experimentation: it is used to split the data set, as well as scale features and perform simplified model evaluation. This utility complements the prerogative of TensorFlow by standardizing preprocessing and performance assessment.

E. Model Persistence and Deployment

Pickle: Pickle was used for serialization and saving of the trained model for possible and rapid loading into memory during deployment, thus minimizing computational overhead. Streamlit: Streamlit was used for developing an interactive scientific web application capable of predicting TEC in real time; relaying Python scripts directly into the interface greatly Teases deployment.

F. Version Control and Collaboration

Git: Git was chosen for version control and collaborative software development. It helped to keep the repository clean and organized and that made tracking changes easy and preserved the integrity of the code.

G. Exploratory Data Analysis

Jupyter Notebooks: Jupyter notebooks were employed for exploratory data analysis. Jupyter offers an interactive environment in which to weave source code and visualizations with markdown documentation together, offering clarity during data exploration and model design.

H. Other Libraries and Tools

OS and Glob Libraries: This library was the instrument that facilitated the automation of file-handling tasks, like populating datasets from directories.

Joblib: Joblib was adopted to carry out the parallelization process during data preprocessing, which among other things made them efficient in processing.

Keras: Keras, which is an API of TensorFlow, provided means for an easier implementation of building and training neural network models.

I. Hardware and System Requirements

Process Units: Multi-core processors and GPUs also played a role in handling the computational demands inherent in training deep learning models. Also, TensorFlow in conjunction with GPU acceleration allows for considerably less time taken to train the models.

Memory Management: Memory was very much a necessity in order to handle bigger data sets in a highly efficient manner during processing.

IV. RESULT AND DISCUSSION

The proposed system for predicting Total Electron Content (TEC) demonstrated a structured and efficient workflow, as depicted in the flowchart and Data Flow Diagram (DFD). The flowchart outlines the sequential stages of the system, starting from user registration and login to collecting space weather data and preprocessing it for model training. The evaluation phase ensures that the model meets performance benchmarks before generating TEC predictions. If the model's performance is deemed acceptable, it proceeds to real-time predictions and report generation, enhancing user accessibility through an intuitive interface. The Data Flow Diagram (DFD) further details the relationships between key system components, including data collection, processing, and storage.

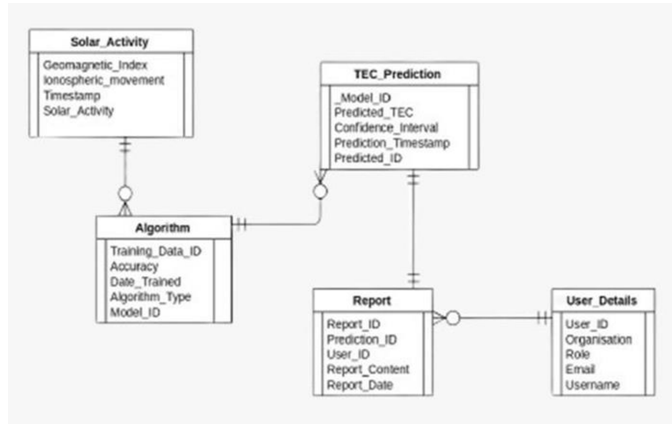

Fig. 1. Data Flow Diagram

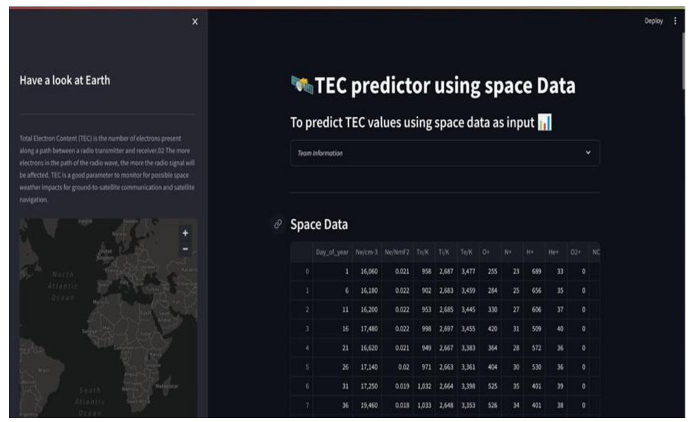

Fig. 2. Website Interface

For instance, the Solar_Activity entity captures geomagnetic and solar parameters, which are used to train the predictive algorithm. This data is linked to the TEC_ Prediction entity, which stores results along with associated confidence intervals. User-specific information, stored in the User_Details entity, facilitates personalized interaction with the system. Generated reports, captured by the Report entity, allow users to analyze prediction results effectively. This modular design ensures robust data handling, accurate predictions, and a user- friendly approach to managing complex ionospheric data. The results validate the system's potential to provide reliable TEC predictions, with future improvements focusing on expanding datasets and optimizing computational efficiency.

V. EXECUTION

The proposed solution is built as a lightweight and self-hostable, open source web interface. The interface is written using the Streamlit framework. Streamlit was chosen because of its rapid development capabilities for AI based projects, and easy to use interface components.

For the model, a pre-trained neural prophet and linear regression-based model. The model is stored in a serialized format using Python's pickle module. This ensures portability, efficient loading and prediction without needing any more training on the user end.

The website is free to use for anyone and is devoid of any login functionality. Users is required to input spatial weather parameters, such as geomagnetic indices, solar flux, and other relevant data, into the interface.

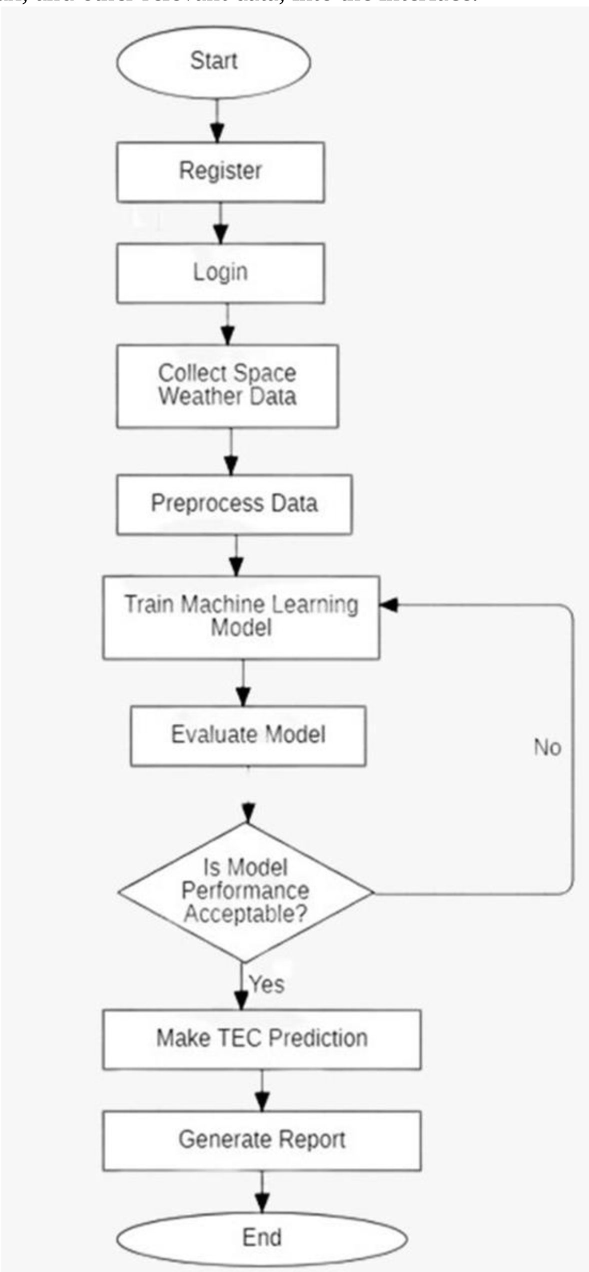

Fig. 3. Flowchart

This data is then processed by the aforementioned AI model to quickly generate TEC prediction data. Due to the model being in a pickle file format, it consumes fewer resources and requires minimal overhead on both the client and server sides. Being a web based solution, it can be easily accessed over any device. This makes the solution not only scalable but also useful without needing any installation or special hardware. Making it accessible to everyone ranging from researchers to students.

Fig. 4. Website Interface

VI. TECHNOLOGICAL ADVANCEMENT

The evolution of ionosphere Total Electron Content predictions has flowed from developments in artificial intelligence, machine learning, and data-driven techniques. The other method of making predictions, empirical equations, and statistical approaches like ARIMA, tended to be less flexible and unable to adapt to unpredictable ionospheric states. The development of deep learning models like LSTM and NARX has been significant in that predictions had a large run-up in accuracy by exploiting the intense temporal dependencies for variation in TEC. The research exploits both Neural Prophet and Linear Regression in combination to maximize prediction effectiveness. Our web-based platform links research and real- world applications by offering interactive visualizations, real- time forecasts, and user-friendly access to TEC insights. It is set to put this innovation as a paradigm shift away from static model-based approaches towards dynamic and AI-powered solutions that are more reliable in aerospace, telecommunications, and defense.

VII. CONCLUSION

The research highlights the effectiveness of using AI for prediction of TEC based on space weather data. By using the pre-trained neural prophet and linear regression based model within an easy to use web interface powered by Streamlit, we have created a tool that makes TEC prediction available to a vast range of users, including researchers, students, and industry professionals. Being a web solution it can be accessed from any device without special hardware requirements.

As the system uses a pre-trained model in form of a pickle file, it makes the system easy to deploy and switch the model in future. Having no login removes any gatekeeping from the platform, making data easily accessible for anyone to use. The system is light on resource usage and hence sustainable and scalable. The developed solution addresses multiple challenges in satellite communication, navigation, etc. . . Moving forward, the solution can be expanded for real-time data integration and region-specific adaptability. The project will help in future studies of the ionosphere and related fields.

REFERENCES

[1] Y. Yang, X. Zhang and Z. Zhao, "An Ionospheric TEC Prediction Method Based on Convolution Operation and LSTM Neural Network," 2024 3rd International Symposium on Sensor Technology and Control (ISSTC), Zhuhai, China, 2024, pp. 398-402, doi: 10.1109/ISSTC63573.2024.10824085.

[2] Y.i. Han, L. Wang, Fu. Wenju et al., "Machine Learning-based short-term GPS TEC forecasting during high Solar activity and magnetic storm periods [J]", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2022b, vol. 15, pp. 115-126.

[3] Z C WEN, S H LI, L H LI et al., "Ionospheric TEC prediction using Long Short-Term Memory deep learning net work [J]", Astrophysics and Space Science, vol. 366, no. 1, pp. 3, 2021.

[4] LI Lei, LI Jing and YANG Chen, "Short-Term Ionospheric TEC Prediction Based on KF-LSTM Combination Model [J]", Journal of Geodesy and Geodynamics, vol. 43, no. 10, pp. 1020-1025, 2023.

[5] Jun Tang, Lang Xu, Xuequn Wu and Ke Chen, "A Short-Term Forecasting Method for Ionospheric TEC Combining Local Attention Mechanismand LSTM Model [J]", IEEE Geoscience and Remote Sensing Letters, pp. 1001305, 2024.

[6] R X Tang, F T Zeng, Z Chen et al., "The comparison of predicting storm-time ionospheric TEC by three methods: ARIMA LSTM and Seq2Seq [J]. Atmosphere", vol. 11, no. 4, pp. 316, 2020.

[7] R X Tang, F T Zeng, Z Chen et al., "The comparison of predicting storm-time ionospheric TEC by three methods: ARIMA LSTM and Seq2Seq [J]. Atmosphere", vol. 11, no. 4, pp. 316, 2020.

[8] L. Liu, S. Zou, Y. Yao and Z. Wang, "Forecasting global ionospheric TEC using deep learning approach", Space Weather, vol. 18, no. 11, pp. 2020, Nov. 2020.

[9] Qiaoli Kong, Yunqing Huang, Xiaolong Mi, Qi Bai, Jingwei Han, Yanfei Chen, Shi Wang, A new high-precision short-term ionospheric TEC prediction model based on the DBO-BiLSTM algorithm: A case study of Europe, Advances in Space Research, 2025, https://doi.org/10.1016/j.asr.2025.03.012.

[10] T. Racharla, S. Rajurkar, S. Sakharkar, A. Mishra, and S. Warjurkar, ”Prediction of TEC Variation Using Space Weather Data and AI,” *Int. Res. J. Mod. Eng. Technol. Sci. (IRJMETS)*, vol. 5, no. 4, Apr. 2023.

[11] E. S¸ entu¨rk, ”Ionospheric TEC Prediction Performance of ARIMA and LSTM Methods in Different Space Weather Conditions,” *1st Interconti- nental Geoinformation Days (IGD)*, Mersin, Turkey, Nov. 2020.

[12] I. J. Kantor, E. R. de Paula, and L. F. C. de Rezende, ”TEC Measurements with GPS Data,” *INPE, Aeronomy Division, Sa˜o Jose´ dos Campos, Sa˜o Paulo, Brazil 2022*.

[13] Harsh Khatter, Amrita Jyoti, Rashmi Sharma, Pooja Malik, Rashmi Mishra “Enhancing Network Efficiency and Extending Lifetime through Delay Optimization and Energy Balancing Techniques”, Wireless Personal Communications (2023). https://doi.org/10.1007/s11277-023-10812-7

[14] Y. Liu, J. Wang, C. Yang, Y. Zheng, and H. Fu, ”A Machine Learning-Based Method for Modelling TEC Regional Temporal-Spatial Map,” *Remote Sens.*, vol. 14, no. 21, Nov. 2022.

[15] L. Guoyan, G. Wang, Z. Zhengxie, and Z. Qing, ”Prediction of Iono-spheric TEC Based on the NARX Neural Network,” *Hindawi Math. Probl. Eng.*, vol. 2021, Oct. 2021.

[16] Nandita Goyal, Kanika Taneja, Shivani Agarwal, Harsh Khatter “Malicious Behavior Identification using Dual Attention based Dense Bi-Directional Gated Recurrent Network in the Cloud Computing Environment”, Computers & Security, Elsevier Advanced Technology, March 2025, Vol 154. https://doi.org/10.1016/j.cose.2025.104418

[17] Harsh Khatter, Anil K Ahlawat, “Web Blog Content Curation Using Fuzzy-Related Capsule Network-Based Auto Encoder”, International Journal of Pattern Recognition and Artificial Intelligence, Vol 36 (2), pp.1-30, 7 Jan 2022 (2022). https://doi.org/10.1142/S021800142250001X

[18] M. Nishioka, S. Saito, C. Tao, D. Shiota, T. Tsugawa, and M. Ishii, ”Statistical Analysis of Ionospheric Total Electron Content (TEC): Long- term Estimation of Extreme TEC in Japan,” *Earth, Planets Space*, vol. 73, no. 1, Feb. 2021.

[19] S. Kundu, S. Sasmal, S. Chakraborti, and S. K. Chakrabarti, ”Study the Ionospheric Total Electron Content (TEC) Variation During Geomagnetic Storm in 24th Solar Cycle,” *2020 URSI Regional Conference on Radio Science (URSI-RCRS)*, Feb. 2020.

[20] X. Gao and Y. Yao, "A storm-time ionospheric TEC model with multichannel features by the spatiotemporal ConvLSTM network", J. Geodesy, vol. 97, no. 1, pp. 9, Jan. 2023.

[21] S. Iyer and A. Mahajan, ”Predicting the Ionospheric Total Electron Content Using Adaptive Regression Model,” *2021 6th International Conference for Convergence in Technology (I2CT)*, Apr. 2021.