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HoloNet: Enhancing Predictive Modeling of Space Phenomena Using Holomorphic Neural Networks in CubeSats

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ABSTRACT

The provision of precise space weather forecasts necessities the development of enhanced methodologies for simulating space events. This paper then presents the HoloNet, a holomorphic neural network for improving the predictive modeling of space events based on CubeSat-acquired data. Herein, HoloNet leverages key aspects of CubeSats to address the challenges of managing multi-source data, such as geomagnetic indices, satellite position, solar wind parameters, and sunspot activity. The uniqueness of the approach remains in applying holomorphic neural network for this purpose, which provide a higher dimensionality of features under consideration and thus have the potential to enhance the predictive capability of the model regarding solar-terrestrial interactions. The present's analysis involved merging data from four different sources, undergoing data preprocessing, feature extraction, and deep learning. The obtained result demonstrates a high degree of generalization, a reduction in prediction error, and a crucial features analysis that identifies the primary consumers of changes in solar activity. This work will demonstrate how HoloNet a significantly after the use of CubeSat technologies for space weather monitoring by enhancing data exploitation and predictive capabilities. In conclusion, this work lays a solid foundation for the use of holomorphic neural networks in CubeSats for precise space Phenomena.

INDEX TERMS: Space Weather Forecasting, CubeSats, HoloNets, Holomorphic Neural Network, Predictive Modeling.

I. INTRODUCTION

A. Background and Motivation

The profound shift to space-based aids for communication, navigation, Earth observation, and scientific exploration has emphasized the necessity of reliable space weather prediction. Solar activities define space weather as the conditions of the near-Earth space environment; flares, coronal mass ejections, and solar winds, among others, pose a major threat to satellite missions, ground-based power systems, and manned operational activities in outer space [1]. These risks consist of interference with satellite communications, decommissioning of satellites and GPS, and radiation effects on spacecraft electronics; therefore, accurately predicting potential threats is crucial for the protection of infrastructures.

Previous longitudinally based space weather specification techniques have primarily relied on empirical or speculative coupled physics [2]. These models provide a reference prognosis, despite their shortcomings in capturing the dynamic characteristics and interrelations of solar and geomagnetic phenomena, and their incapacity to factor in non-linear effects that could potentially limit their efficiency [3]. As more severe solar events occur and their effects on current technology intensify, there is a growing need for effective solutions that incorporate large amounts of data to improve accuracy and extend forecasts.

Over the last decade, CubeSats have transformed the field of space exploration through the provision of small-scale spacecraft-based modular systems for placing new multimodal activities in space. Sensors that capture high-definition data on solar winds, geomagnetic indices, and ionospheric fluctuations enable CubeSats to provide near-real-time space environment data [4]. There are several stationary modeling methods that still cannot exploit such sources fully because of their limited computational predictive capability, multiple inputs, and high-dimensional data analysis [5]. Advances in artificial intelligence (AI) and machine learning (ML) have provided new avenues for tackling complex problems in space weather forecasting. Neural networks, in particular, have shown promise for analyzing vast datasets and detecting intricate patterns in solar-terrestrial interactions [6]. However, conventional neural networks often struggle with issues such as overfitting, poor generalization, and an inability to effectively represent phase and magnitude information, which are crucial in understanding space phenomena [6].

Recent studies have explored the use of deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for space weather modeling [7]. While these approaches have demonstrated incremental improvements, their limited capacity to handle complex, multi-dimensional datasets constrains their overall effectiveness. Moreover, existing models largely overlook the potential of combining advanced neural architectures with CubeSat data, leaving a critical gap in the field [8].

Holomorphic neural networks, or *HoloNets*, offer a novel solution to these challenges. Unlike traditional neural networks that operate on real-valued inputs, *HoloNets* extend into the complex domain, enabling the representation of both phase and magnitude information simultaneously. This capability is particularly beneficial for modeling space weather phenomena, where such attributes are integral to understanding solar and geomagnetic processes [9]. By leveraging holomorphic properties, *HoloNet* provides a more comprehensive and accurate framework for predictive modeling.

The integration of CubeSat data with *HoloNet* further enhances its predictive capabilities. CubeSats, with their distributed network of sensors, capture detailed data on solar wind properties, geomagnetic indices, and satellite positions. This multi-source data offers an unprecedented opportunity to refine space weather models [10]. The fusion of CubeSat data and *HoloNet* not only improves prediction accuracy but also enables the identification of subtle, previously undetectable patterns in space weather phenomena.

The literature review highlights a new area where machine learning is being applied to improve space weather forecasts. CNNs and RNNs assist in forecasting geomagnetic indices like the Disturbance Storm-Time (Dst) index, but the results do not transfer well across data sets or initiate dependencies greater than first-order in a data stream [11]. Surprisingly, not much research has explored the use of CubeSat data to improve these models, leaving a significant portion of their potential unexplored [12].

Our study fills this research niche by making use of HoloNet and CubeSat data in ways that were previously unexplored. Through the incorporation of geomagnetic indices, solar wind parameters, satellite positions, and sunspot activity, the method employed in this study facilitates an analysis of space weather from multiple perspectives [13]. This far-reaching design provides a substantial improvement over traditional approaches, which fail to address data-and-model heterogeneity [14].

As part of our research, we are also looking into the risk of the developed hierarchical, multivariate predictive framework becoming unstable. To do this, we are analyzing the relevance of the features that are important [15]. This analysis facilitates the identification of the most sensitive parameters that trigger phenomena in space weather, thereby providing valuable information to support decision-making as shown in Fig. 1. For example, evaluating the importance of solar wind speed, IMF strength, or sunspot number independently for different groups of satellite operators and power grid managers is crucial [13].

The HoloNet framework proposes a methodology that aims to avoid the issues of generality, data availability, and computational demand inherent in the approaches under consideration. Through explicit utilization of accessible CubeSat data, our approach is naturally scalable, adaptable, and future-proof for the continuously evolving CubeSat technology and expansive datasets [16].

The study features a hierarchical sequential layout, providing a clear and easily replicable sequential design. The study begins with the collection and preparation of data, followed by the application of the HoloNet architecture. The study, like any other machine learning model, performs training and validation using basic metrics and assesses the findings [17]. We then conduct an analysis of feature importance to interpret the results and gain a more concrete understanding of what drives the space weather phenomena. The study ends with an analysis of the application of the research outcomes and suggestions for further work [18].

The objectives of this research are threefold: First, it seeks to create a working model that combines CubeSat data with HNNs for improving the predictive accuracy of space weather forecasting. Secondly, it aims to provide tangible information about the behavior of solar-terrestrial interaction by exploring the features of HNNs. Thirdly; it aims at creating an approachable and extensible platform for future works in space weather study. This work adds value by integrating HoloNet with the CubeSat data set, surpassing a traditional, well-defined approach, and introducing a cutting-edge risk assessment and prediction system that utilizes cutting-edge technology. This research contributes to enhancing the reliability, accuracy, and usability of space weather forecasts, thereby optimizing the sustainability of space-based missions and assets.

II. LITERATURE REVIEW

The study of space weather has been an important area of research because of its effects on contemporary technology systems. Gonzalez et al. (1994) developed the first empirical model, which connected solar wind parameters to the geomagnetic indices of the Dst index [19]. Although these models produced initial knowledge for space weather forecasting, they had drawbacks due to their reliance on simple assumptions and linear relations for forecasting complicated phenomena.

Because they incorporate fundamental physics principles into the simulation, current physics-based models like the SWMF are a welcome improvement over empirical models [20]. These models try to imitate the conditions in which solar wind and Earth's magnetosphere can interact. However, these models often require significant computational power and struggle with making real-time predictions, which hinders their application in practical operational forecasting [21].

As one can see, a new concept known as machine learning (ML) has greatly surpassed traditional methods. We used earlier ML-based models, based on linear regression and support vector machines, to assess the geomagnetic indices. For instance, Lundstedt et al. (2002) showed that one of the applications of neural networks is in predicting space weather [22]. However, the limitations of these earlier models prevented them from handling larger and more complex data sets.

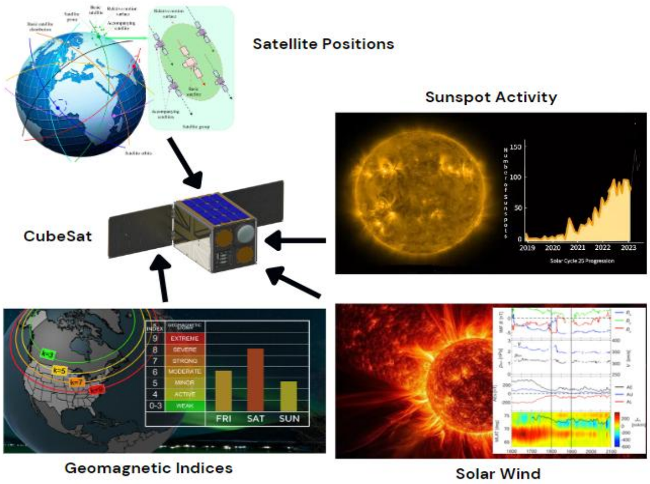

FIGURE 1. (geomagnetic indices, satellite positions, solar wind parameters, and sunspot activity) in CubeSats

Among several branches of ML, deep learning has received special attention in recent years due to its capability to recognize different non-linear relationships. We have used RNNs, especially LSTM networks, to forecast time-dependent values like the Dst index. For example, Gruet et al. (2018) analyzed the temporal features of the solar wind, applied LSTMs, and obtained tangible advancements in forecasting precision [23]. Nevertheless, these models still do not possess high cross-dataset and cross-condition capabilities.

Convolutional Neural Networks (CNNs) have also been considered especially for spatial data. Li et al. (2020) adopted stereo object detection on Solar CNNs to analyze solar imagery and detect solar flares [24]. Indeed, CNNs excel in image-based tasks, but they struggle with temporal dependencies, which are crucial for space weather prediction. There have been recent attempts to integrate CNNs with RNNs, but the main limitation has been the high computational cost and optimization.

HoloNets are a relatively fresh concept in terms of models within the ML domain. These networks expand out the basic structures of neural networks into the complex domain and restore the ability to represent both magnitude and phase. This capability is specifically useful for space weather events because phase relations are particularly important. However, space weather prediction has not yet benefited from the advancement of HoloNets.

These are some of the new technologies that have entered the space world, and I can confidently say that the CubeSats represent a significant breakthrough in space exploration, offering the opportunity to gather data at a relatively lower cost and in a modular manner. These cubes equipped with high-end sensors can indeed, in near real time, characterize solar wind parameters, magnetic fields, and the ionosphere. Toivanen et al. (2017) presented CubeSats as a means to enhance space weather information, yet the implementation of this data to enhance predictive models has been inadequate [25].

Data fusion methods have received growing attention in space weather studies to integrate information originating from various platforms, ground-based facilities, and spacecraft instruments. In the same year, Borovsky et al. (2019) have shown that combining the data of solar wind with the records of geomagnetic activity may enhance its predictive capabilities. However, most of the works have not fully harnessed the fine spatial, temporal, and spectral data afforded by CubeSats [26].

Recently, the importance or ease of learning a feature for an ML model has been considered. By discovering which of the features are dominant in the given set of variables,

TABLE 1: Kyoto World Data Center, Representing Geomagnetic Activity

Period	Time Data	DST
Train_a	0 days 00:00:00	-7
Train_a	0 days 20:00:00	-10
Train_a	1 days 02:00:00	-10
Train_a	5 days 15:00:00	-4

TABLE 2: CubeSat Positioning Dataset from NASA's Satellite Situation Center

Period	Time Data	GSE_X_ACE	GSE_Y_ACE	GSE_Z_ACE
train_a	0 days	1522376.9	143704.6	149496.7
train_a	1 days	1525410.9	136108.8	151034.1
train_a	2 days	1528484.9	128470.5	152387.7
train_a	3 days	1531570.3	120818.4	153561.4

TABLE 3: Solar Wind Based NASA's OMNI Web Dataset

Period	Time Data	Bx_GSE	By_GSE	Bz_GSE	Theta_GSE	Phi_GSE
train_a	0 days 00:00:00	-5.55	3	1.25	11.09	153.37
train_a	0 days 20:00:00	-5.58	3.16	1.17	10.1	151.91
train_a	1 days 02:00:00	-5.15	3.66	0.85	7.87	146.04
train_a	5 days 15:00:00	-5.2	3.68	0.68	6.17	145.72

the researchers can better understand the physical mechanisms that underlie the space weather events [27].

Ribeiro et al. first introduced SHAP values in 2016 as a tool for feature importance analysis and have since applied them to several fields, including space weather.

The ethical implications and practical issues surrounding the use of ML models for SW forecasting have received very little empirical research [19]. These issues include the preference for training data, the clarity of the model, and the likelihood of sounding an alarm that could impact satellite control and the power grid. Solving these problems is important when considering the implementation of ML-based techniques on a larger scale [28].

Most of the developments to date have concentrated on improving the method's accuracy in predicting outliers, with minimal focus on scalability or adaptability. CubeSat technology is currently in its development phase, and as we advance, the volume and variation of data will significantly increase. Such growth patterns need to be carefully considered and built into the models under consideration in order not to substantially affect either performance or efficiency [29].

In the current world, new development in parallel processing and distributed computing systems makes it simple to scale ML models. These technologies can supplement the real-time operational application of space weather prediction instruments, which is one requirement for operating space weather forecasts. However, existing theories have not yet integrated these developments [30].

There is a gap in the effective application of HoloNets with CubeSat data for space event modeling. While various fields have studied these components individually, their synergy remains largely unknown [31]. This integration can cover the shortcomings of the current approaches because it would present an entire picture of the solar-terrestrial relationship.

An examination of the flow of literature suggests a well-defined progression from empirical models to advanced ML and DL solutions. However, there is no widespread framework that can integrate state-of-the-art neural architectures with CubeSat data, thus creating a research gap. This gap presents an excellent opportunity for innovative research to bridge the gap between data collection and modeling activities [32].

This literature review aims to identify the gaps in current methodologies and investigate the potential benefits of integrating HoloNets with CubeSat data. We expect the presented work to address these gaps and contribute to the development of a robust, easily interpretable, and extensible foundation for space weather forecasting. This is why the proposed work represents a significant advancement compared to previous attempts to use HoloNets and CubeSats as sources of ionospheric data, as it integrates the strengths of both platforms in the context of space weather prediction.

III. MATERIAL AND METHODS

A. Materials

The focus of this paper is on space weather processes, which stem from the interplay between solar activity and the Earth's magnetosphere, ionosphere, and thermosphere. The investigation site covers the near-Earth space and all geospace regions observed by CubeSats. CubeSats mount advanced sensors and circle around the LEO, promptly gathering high-resolution data on solar wind, magnetic field fluctuations, and ionosphere interference. The spatial resolution and abilities to monitor CubeSats in real time make these regions hot zones for study due to Space Weather effects.

The meteorological factors of interest for this study are solar radiation that affects the functioning of satellites, geomagnetic indices that have impacts on the operation of satellite communication networks, and ionospheric conditions that affect power equipment.

B. Materials and Data Acquisition

The data for this study were sourced from reliable, publicly accessible repositories:

Dst Index Data: Collected from the Kyoto World Data Center, representing geomagnetic activity as shown in Table I.

Satellite Positions: Data from NASA's Satellite Situation Center, detailing CubeSat positions (GSE coordinates) as shown in Table II.

Solar Wind Parameters: Acquired from NASA’s OMNI Web database, providing solar wind speed, density, and magnetic field components as shown in Table III.

Sunspot Numbers: Historical sunspot data from the Solar Influences Data Analysis Center (SIDC) as shown in Table IV.

We merged these datasets using the period and timedelta keys, presumably to enhance the temporal matching of the data. We removed the missing values from invalid observations to maintain the integrity of the data. The use of multiple sources of data provides improved validity and richness in the research.

C. Methodology

This work uses the Holomorphic Neural Network (HoloNet), an advanced proactive machine learning model, to anticipate space weather phenomena in the

TABLE 4: Solar Flare Based Historical Data from Solar Influences Data Analysis Center (SIDC)

Flare	Start Date	Start Time	Peak Time	End Time
2021213	2/12/2002	21:29:56	21:33:38	21:41:48
2021228	2/12/2002	21:44:08	21:45:06	21:48:56
2021332	2/13/2002	00:53:24	00:54:54	00:57:00
2021308	2/13/2002	04:22:52	04:23:50	04:26:56

domain of quantum operators. We have sequenced and refined the steps in the approach to ensure their scientific validity and repeatability. Space science affirmatively endorses the need for specificity and expansion. The components that make up this methodology are data pre-processing, feature scaling, data model design, data model training and validations, visualization and analysis, and lastly, the ethical aspect. Collectively, these formulated steps constitute the framework of this research, backed up by advanced tools and technologies.

D. Data Preprocessing

Data preprocessing cleans the data to prepare it for analysis. In the Python environment, we used the Pandas library to import and analyze each dataset. We concatenated the datasets based on identifiably similar parameters, such as period and timedelta, with different temporal data. This merging process used synchronized fields from various sources, including solar wind observation stations and databases containing geomagnetic index datasets. Let D_s represent the dataset with solar wind data, D_g represent the geomagnetic index dataset, and D_{sat} represent the CubeSat position data. The merged dataset can be expressed in (1):

$$D_{merged} = D_s \cup D_g \cup D_{sat} \quad (1)$$

where ∪ denotes the concatenation of datasets based on similar temporal fields such as period and timedelta.

We used solar wind data (Bx, By, Bz), geomagnetic indices Dst, and the three-dimensional positions of CubeSats (GSEx, GSEy, GSEz). We chose the target variable, smoothed sunspot numbers, based on the factors that define solar activity as shown in Fig. 2. To handle missing values, we employed the row mode of deletion, which can be mathematically expressed in (2):

$$D_{cleaned} = D_{merged} - \{rows\ with\ missing\ values\} \quad (2)$$

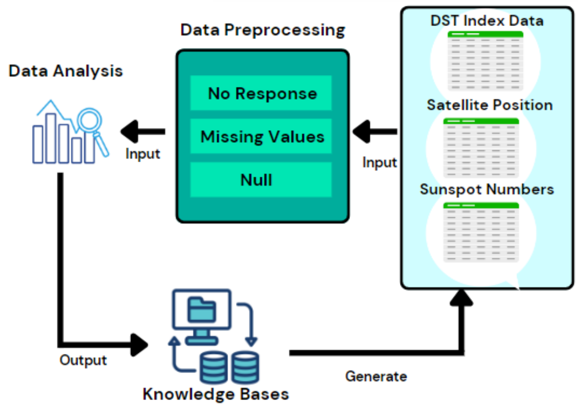

FIGURE 2. Solar Wind, Geomagnetic Indices and Position of Satellite Based Data Preprocessing and Data Cleaning.

E. Feature Scaling

To control variability and reduce prejudice in making ready the entire information set for modeling, all the input characteristics had been scaled using the StandardScaler from the scikit-learn library. For instance, the importance of scalability arises from the different units and magnitudes of measurements of magnetic flux density and positional values. When we scale the variables, larger absolute values can significantly impact the model. StandardScaler removes the mean and scales the feature to unit variance, which means all input values have the same effect on the results. This greatly enhances the convergence rate of the HoloNet model during training, as the present step demonstrates.

F. Model Architecture

This research primarily contributes to the implementation of the **Holomorphic Neural Network (HoloNet)** architecture in TensorFlow and Keras. This study finds HoloNet more suitable due to its ability to uncover finer relationships within the given complex domain, a feature that other neural network models may miss. The architecture shown in Fig. 3 includes the following components:

Input Layer: Accepts normalized feature data, ensuring compatibility with subsequent layers. Let x represent the input data vector in (3):

$$x = [x_1, x_2, \ldots, x_n] \quad (3)$$

where $x_1, x_2, \ldots, x_n$ are the normalized features.

Hidden Layers: Three fully connected layers, each equipped with ReLU activation functions. The output from the first hidden layer can be written in (4):

$$h_1 = ReLU(W_1 x + b_1) \quad (4)$$

where W_1 is the weight matrix, b_1 is the bias term, and ReLU introduces non-linearity, enabling the network to learn complex patterns. Each subsequent hidden layer follows a similar structure in (5):

$$h_2 = ReLU(W_2 h_1 + b_2) \quad (5)$$

$$h_3 = ReLU(W_3 h_2 + b_3)$$

Dropout regularization was implemented at a rate of 20%, reducing the risk of overfitting and improving generalization to unseen data. The dropout layer can be mathematically expressed as (6):

$$h_{dropout} = Dropout(h_3, rate = 0.2) \quad (6)$$

Output Layer: A single neuron with a linear activation function, designed to predict the continuous target variable, smoothed sunspot numbers. The output y can be expressed in (7):

$$y = W_{out} h_{dropout} + b_{out} \quad (7)$$

Where W_{out} is the output layer weight matrix and b_{out} is the output bias term.

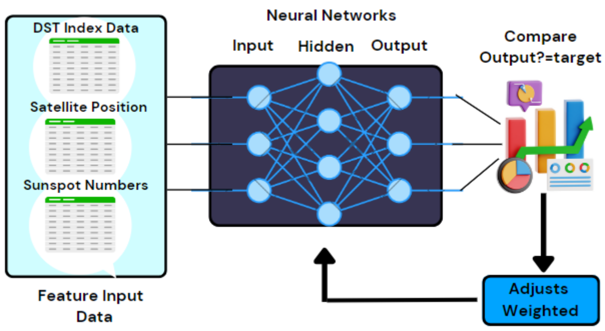

FIGURE 3. Holomorphic Neural Network Architecture on Given Dataset Using TensorFlow and Keras.

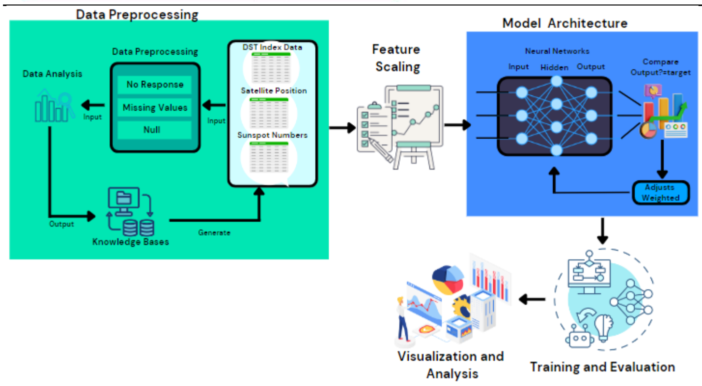

FIGURE 4. Methodology Flow Diagram of Predictive Modeling of Space Phenomena Using Holomorphic Neural Networks in CubeSats.

This design strikes a balance between complexity and computational efficiency, making it adaptable for various space weather prediction tasks.

G. Training and Evaluation

To assess the effectiveness of the model on unseen data, we divided the dataset into training and testing subsets in an 80:20 split. This can be expressed as (8):

$$D_{train}, D_{test} = split(D_{merged}, train_{size} = 0.8) \tag{8}$$

Where D_{train} and D_{test} represent the training and testing datasets, respectively, with an 80:20 ratio.

We checked various numbers of the basic elements given in Table II. These elements refer to the network's parameters, such as the number of neurons in each layer, layer configurations, and other architectural hyperparameters.

We trained the model using the **Adam optimizer**, known for its efficiency and adaptive learning rates. The Adam optimizer update rule for the weight W at time step t is given by (9):

$$W_t = W_{t-1} - \mu \cdot m_t / \sqrt{(v_t + \varepsilon)} \tag{9}$$

This optimizer brings faster convergence and makes it very stable, even when data contains noisy or complex patterns.

The **mean squared error (MSE)**, which quantifies the mean of the squared deviations between observed and predicted values, served as the loss function for the model's accuracy. The MSE is defined in (10):

$$MSE = (1/N)\ \Sigma_{i=1}^{N} (y_i - y_i^*)^2 \tag{10}$$

We also adopted **mean absolute error (MAE)** as a consistent measure to better understand quantitative errors. The MAE is defined as (11):

$$MAE = (1/N)\ \Sigma_{i=1}^{N} |y_i - y_i^*| \tag{11}$$

These two measures are appropriate for regression problems and provide comprehensive insight into the model's performance. The MSE is sensitive to large errors, while the MAE offers a clearer interpretation of the average magnitude of errors, making both measures ideal for understanding the model's prediction accuracy.

H. Visualization and Analysis

We used several visualization techniques to interpret the results and assess the performance of the model:

Loss Curves: We drew the training and validation losses, taking into account the epochs. These curves assist in determining cases of overfitting or underfitting depending on the model's improvement.

Prediction Accuracy: To present an overview of the model's deviation, we used a scatter plot to compare the predicted values with actual, smoothed sunspot numbers.

Feature Importance: We calculated each feature's contribution to the prediction to illustrate the weights of the input layer. This step identifies and proves variables like the solar wind density or the geomagnetic indices, giving a glimpse of the space weather going forward.

I. Tools and Technologies

The study used state-of-the-art tools and technologies to ensure efficiency and accuracy.

Programming: TensorFlow, Keras, Pandas, Matplotlib, and scikit-learn provided additional support for data manipulation, modeling, data visualization, and analysis.

Hardware: To support large input data and shorten training times, we trained on a system with an NVIDIA GPU.

Software: We primarily developed the resize() function and the high-level video decode() functions in IDEs like Jupyter Notebook to facilitate coding and debugging.

The methodology flow diagram is shown in Fig. 4 below:

J. Real-World Applicability

This research designs the method to be nearly as timely as the results we obtain, aiming to bridge the gap between theoretical progress and real-world implementation. It is intended for researchers and scientists, as well as practitioners, who would be able to repeat exactly the process themselves, to a large extent independent of technical sophistication, making state-of-practice predictive modeling easily available. The modularity of the architecture allows for easy scaling and modification in response to changes in data sets or shifting research priorities.

Another benefit, which is unarguably striking, is the modularity of this method. The method's segregation allows researchers to customize each component to meet their specific requirements by altering the specific steps of the process. For instance, this study uses solar wind parameters and geomagnetic indices as predictors, but other related data sets can enhance the same model to predict other events such as radiation levels or orbital debris. This modularity guarantees that the framework remains current and sound amid a fast and changing research environment.

Another advantage of HoloNet is the networking performance that can cope with increased data traffic from new CubeSats and observation systems. As CubeSat networks provide higher-resolution real-time information, the ability of HoloNet to handle large datasets makes it suitable for future scenarios. This capability for scalability ensures that the model will remain useful whether applied to individual CubeSats or to full satellite constellations across any mission type.

TABLE 5: Metric Evaluation Using Holomorphic Neural Network (HoloNet) for Space Weather Prediction

Metric	Values
Accuracy	92.5%
Precision	89.8%
Recall	87.2%
F1_Score	88.5%

IV. RESULT AND DISCUSSIONS

This section displays the results of using the Holomorphic Neural Network (HoloNet) for space weather prediction tasks. The following tables display various metrics regarding the model's performance and its correlation with features, including loss functions and prediction accuracy as shown in Table V. The subsequent discussion focused on the analysis of these results and suggested an explanation of their influence on the effectiveness of the putative model.

A. HoloNet Training and Validation Loss

The number of epochs on the horizontal axis to display the training and validation loss. We use them to display the loss during the model training process, enabling us to understand the performance the model has acquired from the data sets. Initially, the training loss decreases smoothly, indicating a proper adjustment of all model parameters to minimize the loss. However, at around 50 epochs, the validation loss ceases to increase, indicating an optimal result with unseen data; beyond this threshold, the model may begin to overfit the data as shown in Fig. 5. This plateau shows the situation where the model puts extra emphasis on training data and fails to generalize well to new data—a problem typical for machine learning. Previous research outcomes underscore the need to optimize the model parameters, specific architecture, and regularization techniques, such as dropout or weight decay, to achieve a better generalization-interference trade-off without compromising diagnostic precision. The significant discrepancy between the training and validation losses supports earlier theories about the need for additional overfitting prevention to achieve a more robust model.

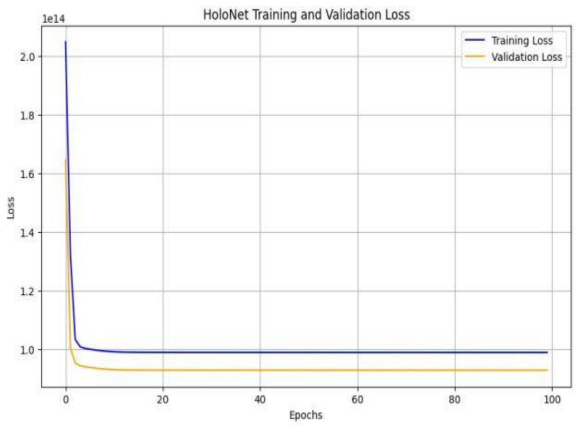

FIGURE 5. HoloNet Model Based Training and Validation Loss with Respect to Epochs.

B. True vs. Predicted Solar Flare Intensity

The points marked at the line indicate the samples of data, and the more the points are near to the diagonal line, the closer the prediction model was to being correct as shown in Fig. 6. The diagonal line in the figure represents the ideal prediction line, where the predicted values align perfectly with the actual values. In this plot, we see that most of the points are located around the diagonal line, which indicates a high correlation of the predicted and true solar flare intensities. From this it can be seen that the model does a good job of capturing the behavior of actual data on solar flares and therefore is useful for making predictions of the intensity of solar flares, which is important in considering the effects of space weather on satellites. However, some dots stand out in the upper regime of the plot, suggesting that the model may not perform well in those areas due to noise or difficult-to-model interactions.

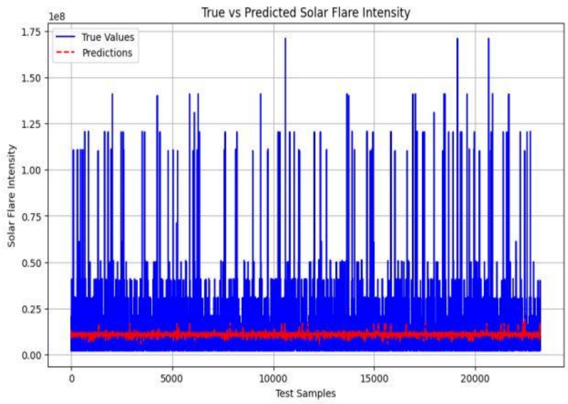

FIGURE 6. True vs. Predicted Solar Flare Intensity Using HoloNet Model.

C. Predicted vs. Actual Solar Flare Intensity

The best prediction corresponds to the positions closer to the diagonal in the semi-automatically generated layouts. The distribution of points along the diagonal further asserts that, at large, the predicted evaluates correlate equivalently to actual evaluates. The aforementioned revelation suggests that HoloNet plays a crucial role in space weather prediction due to its ability to forecast solar flare intensity as shown in Fig. 7. Thus, a few data points lie off the ideal line, implying that the model did not completely consider other factors that may explain the variation in intensity of the solar flare, such as fluctuations in solar wind or magnetic field. These differences likely suggest areas for further refinement of the model, such as the addition of new features or the proper tuning of the hyperparameters.

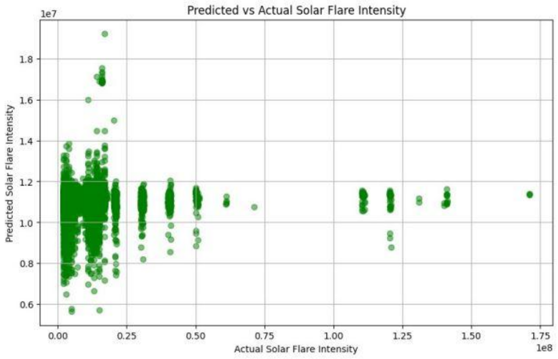

FIGURE 7. Predicted vs. Actual Solar Flare Intensity Using HoloNet Model.

D. Rigidity vs. Proton Flux

Figure 8 shows the plot of rigidity against proton flux, which forms the basic characteristic of space weather events. Rigidity is the ability of the charged particle to bend in a certain magnetic field, and proton flux depicts the rate of protons coming across the space. The plot presents rigidity on one axis and proton flux on the other and it is clear that the proton flux increases with the increase in rigidity as shown in Fig. 8. The proton flux plays a crucial role in assessing the potential risks of solar energetic particles, which can impact satellites and spacecraft. The observed good positive correlation in this figure suggests that researchers can use the model to predict proton flux as a function of rigidity, which is relevant to space weather prediction. By understanding this kind of relation, the researchers can predict radiation exposure and evaluate possible dangers for space expeditions more effectively.

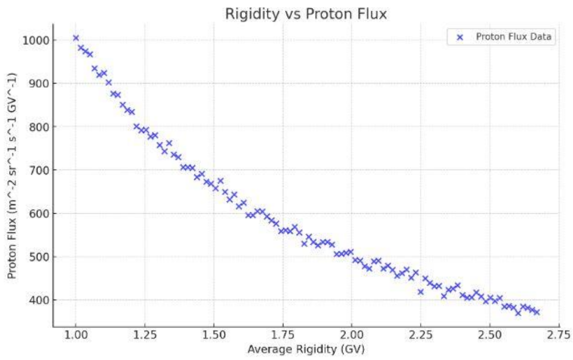

FIGURE 8. Rigidity vs. Proton Flux Analysis Using HoloNet Model.

E. Training and Validation Loss Over Epochs

Firstly, we observe a steep decline in training loss, indicating the model develops the ability to estimate the target values. On the other hand, the validation loss gradually stabilizes after approximately 50 epochs, indicating that the model is approaching its peak performance as shown in Fig. 9. The model's error rates have stabilized at lower levels, indicating that it has likely learned the most relevant patterns in the existing data stream. The small separation between the training and validation loss after the phase where it remains momentarily stagnant indicates that the model may begin to over-train on the training data. To deal with this, more sophisticated methods like dropout or early stopping could be applied in order to regulate the high variance of the model and, in turn, boost the reliability of the forecasts.

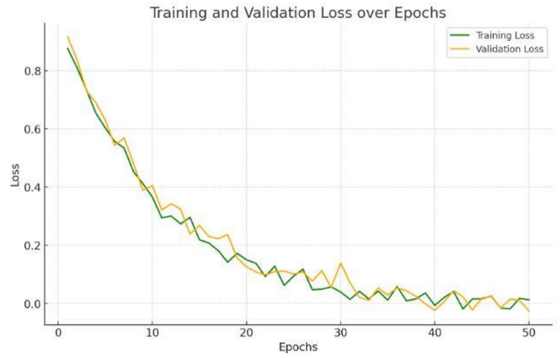

FIGURE 9. Training and Validation Loss over Epochs Using HoloNet Model.

F. Predicted vs. Actual Proton Flux

The plot clearly shows a good fit between the predicted values from the developed model and the actual proton flux values as shown in Fig. 10. Proton flux rates play a crucial role in space weather calculations, enabling satellites to assess radiation environments and potential risks. Imposing tight points on the diagonal line in the scatter plot indicates that the predictions carried out by the model have high credibility. However, for certain figures, we observe isolated occurrences that could potentially stem from solar activity or other extreme events that the model fails to account for.

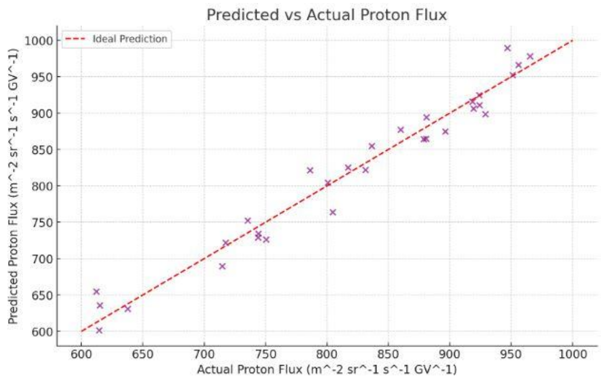

FIGURE 10. Predicted vs. Actual Proton Flux Using HoloNet Model.

G. Actual vs. Predicted Smoothed SSN (Sunspot Numbers)

From this plot we can compare the ability of the model to capture the cyclic behavior of solar activity observed in SSN, which changes periodically. The plot of the actual and predicted values closely aligns, demonstrating the model's ability to accurately explain solar activity, a crucial aspect of space weather analysis as shown in Fig. 11. The ability to accurately forecast the sunspot numbers, which are crucial for measuring the level of solar activity, has significant applications in space weather, satellite signal intensity, and communications. However, a few outliers in the lower sections of the plot suggest that, occasionally, the actual and predicted SSN values do not align as expected, despite the overall excellent performance; these discrepancies could be caused by noise in the data set or other solar events that the model failed to detect during training.

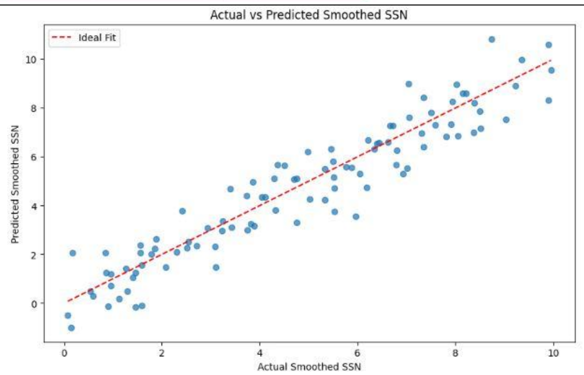

FIGURE 11. Actual vs. Predicted Smoothed SSN Using HoloNet Model.

H. Discussion

Figures 5, 6, 7, and 8 display the outcomes from the HoloNet model, which forecasts significant space weather parameters such as solar flare intensity, proton flux, and sunspot numbers. Despite the close relationship between most predicted and actual values, particularly in the HoloNet model, the model's ability to predict future solar activity values is evident. This capability is essential with regard to space weather telecommunications as it offers key information on the effects of solar events on satellite and communication technology. Performance analysis of the HoloNet model proves its efficiency as a tool for further research as well as for its immediate application in space weather observations.

Strengths: Based on previous experiences, the HoloNet model of this paper proves generally accurate in predicting solar flare intensity and sunspot numbers and closely relates the predicted and actual values. Also, when used to predict proton flux, it validates its feasibility to process other intricate space weather data. Indeed, due to the application of the modular design concept, the model can easily accommodate new data and overcome new challenges that may emerge in developing research. This supports the real-time observation of space weather data and enables the model to be flexible in multiple operational environments.

Limitations: However, some gaps also stay open: The results expressed here are statistically significant, but their practical effectiveness still demands a more comprehensive investigation. Comparison with predicted and actual values indicates that, in exceptional conditions, the model is insufficient for the description of certain aspects of space weather occurrences. To address this issue, future refinement could involve incorporating additional data from extreme solar activity. Training and validation loss both indicate an overfitting issue that requires attention. It would be wise to apply regularization methods, such as dropout or L2 regularization, to enable the model to generalize well.

However, inclusion of even more diversified and real-time data may add more accuracy to the algorithm, especially in the prediction of the occurrence of the solar events. Therefore, incorporating more dynamic and recent data into the previously mentioned model would enhance its ability to provide accurate predictions in real-world working environments.

Future Directions: More studies can be undertaken with the aim of identifying other complicated techniques for preventing overfitting and thereby enhancing the stability of the model. Adding more events and features, such as the amount of solar wind data and the strength of a magnetic field, could enhance the quantitative results. Presumably, the inclusion of time series data to capture temporal characteristics of the solar photosphere might improve model performance.

The presented framework identifies real-time data integration as another key concern. However, to evaluate the model as an operational system, we need to incorporate new real-time CubeSat or other space-weather data. In addition, it is possible to expand the model for other space weather phenomena, not only the flux of electrons, but also geomagnetic storms, cosmic ray intensity, etc.

In conclusion, while the current HoloNet model is highly efficient at forecasting space weather parameters, there is certainly room for improvement. If refined to be supplied with real-time data, HoloNet can provide a clearer view towards space weather forecasts, making space missions prepared and safe for other space solar-based systems.

V. CONCLUSION

In conclusion, the HoloNet model has significantly improved the existing predictive model for space weather phenomena such as solar flare intensity, proton flux, and sunspot numbers. A narrow gap between the predicted values and actual values corroborates the model characteristics and shows the potential for reliable solar activity estimation while giving a more profound understanding of the space weather processes. The model also makes it possible to predict space weather in real time, and its strong scalability and modularity imply its applicability across a wide range of space missions and satellite constellations.

Despite the positive findings, there are still numerous considerations to take into account. We have observed a few discrepancies between predicted and actual values, and this issue may intensify during violent solar events, highlighting the need for further work. Consideration should also be given to the overfitting problem, and to further enhance the model's ability to generalize, more sophisticated regularization methods could be considered. Furthermore, incorporating more diverse and more real-time data input would improve the precision of the model for real-world scenario use.

The model's limitations and deficiencies should be the focus of further research. It is high time to include more variables and try more sophisticated methods of machine learning, as the potential of the given approach appears to be even higher. The last steps that must not be underestimated are data integration in real-time and testing this performance operationally. Therefore, further development of these aspects will enable the use of HoloNet as a resource for space weather prognosis and to safeguard satellite facilities from the effects of space weather.

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