Predicting Geomagnetic Storms with the Use of AI Algorithms in Deep Space Exploration

Manal Siddiqui
Carleton University, School of Computer Science, Ottawa, Canada
manalsiddiqui@cmail.carleton.ca

Michel Barbeau
Carleton University, School of Computer Science, Ottawa, Canada
barbeau@scs.carleton.ca

***Abstract*—This paper presents a predictive model for geomagnetic storm forecasting. The predictive model builds using data on solar wind speed, density, temperature, and magnetic field intensity. When it comes to sequential data, Long Short-Term Memory (LSTM) models typically perform better than other neural network models. LSTM models possess memory cells that improve their ability to identify long-term dependencies in the data and make them ideal for use in weather prediction models. We adopt the LSTM model to detect significant shifts in magnetic field and solar wind to predict early warnings of geomagnetic storms. Forecasting these storms is critical for minimizing any interruptions because they threaten communication networks, power grids, and satellite activities.**

We use data from the National Oceanic and Atmospheric Administration's Deep Space Climate Observatory (DSCOVR) satellite. The DSCOVR satellite currently monitors space weather as it measures the main factors of the solar wind and local magnetic field. These measurements are critical for understanding space weather processes and their effects on Earth.

This paper advances space weather forecasting and shows a direct use of machine learning techniques in space science. The LSTM model's predictive capabilities allow us to better prepare for geomagnetic storm events, protecting technology such as satellites and advancing our knowledge of space weather.

I. Introduction

Geomagnetic storms caused by solar activity pose significant risks to communication networks, power grids, and satellite operations. In a recent study on the impact of geomagnetic storms, it was observed that such storms can cause significant disruptions to satellite operations, including what has been termed "mass migrations" of satellites. In 2024, two major geomagnetic storms led to unprecedented orbital maneuvers, particularly among Starlink satellites in low Earth orbit (LEO). These storms increased atmospheric density at LEO altitudes, resulting in higher drag on satellites, which caused their orbits to decay. As a consequence, nearly 5,000 satellites performed orbit-raising maneuvers in a single day—marking the largest mass migration in history. This phenomenon highlighted the challenges faced by satellite operators, as inaccurate storm forecasts led to position errors of up to 20 kilometers, further complicating collision avoidance efforts. The increased frequency of such maneuvers during geomagnetic events highlights the vulnerability of satellite systems to space weather, emphasizing the need for more accurate space weather models and forecasting to mitigate these disruptions and ensure the stability of satellite operations [1].

This research aims to develop a predictive model using data from National Oceanic and Atmospheric Administration (NOAA)'s DSCOVR satellite to mitigate these risks and advance our understanding of space weather.

The results of the research paper indicate that the Long-Short-Term Memory (LSTM) neural network model, built with data from NOAA's Deep Space Climate Observatory (DSCOVR) satellite, was successful in forecasting geomagnetic storms. The model demonstrated strong training accuracy, ranging from 83% to 84% and a high validation accuracy, ranging from 85% to 86% , indicating its ability to generalize well to unseen data. Training loss decreased steadily, showing improved prediction accuracy over time. Despite some potential overfitting, the model is promising for space weather forecasting, with room for improvement in generalizing and incorporating additional data for better accuracy. The study emphasizes the importance of early geomagnetic storm prediction in protecting satellite infrastructure.

Training accuracy measures how well the model performs with the data it was trained on. This indicates the percentage of correct predictions made by the model for the training dataset during its learning process. A high training accuracy, such as the 83-84% in your paper, means that the model has successfully learned the patterns from the data it was exposed to. In this case, it shows that the LSTM model is effectively capturing the relationships between solar wind parameters (speed, density, temperature, and magnetic field intensity) and geomagnetic storm events. This is a positive sign, where the model has learned to predict the intensity of geomagnetic storms based on the input features of the training data.

In Sec. II, we provide an overview of geomagnetic storms and their impact on communication networks, power grids, and satellite operations, followed by a discussion of the research objective of developing a predictive model using data from NOAA's Deep Space Climate Observatory (DSCOVR) satellite. Sec. III presents the results of the model, highlighting the training and validation accuracies and the importance of early geomagnetic storm prediction. In Sec. IV, we discuss the effects of geomagnetic storms on satellites, including atmospheric drag, damage to solar arrays, and electronic disruptions. Sec. V reviews related work on deep space communication and the integration of AI and machine learning in satellite systems. The methodology, including the NOAA DSCOVR satellite and its data collection instruments, is described in Sec. VI, followed by the pre-processing steps and LSTM neural network model in Sec. VII. Finally, conclusions and future research directions are discussed in Sec. VIII.

II. Effects of Geomagnetic Storms on Satellites

Geomagnetic storms and solar activity lead to harsh radiation environments critical for newly launched satellites. The effects include:

- **Atmospheric Drag**: Solar extreme ultraviolet and Joule heating expand the Earth's atmosphere, increasing drag on low Earth orbit (LEO) satellites, potentially leading to orbital decay and uncontrolled reentry [2].
- **High-Energy Particle Impact**: Charged particles from solar energetic particles (SEPs) and cosmic rays cause displacement damage in solar arrays, reducing efficiency and leading to power loss.
- **Electronic Disruptions**: Charged particles can penetrate electronic components, causing single-event effects, ionization, increased noise, power consumption, and potential component failure [2].

Section III reviews related work.

III. Related Work

The research I did prior to this focused on adapting communication methods for deep space missions, addressing challenges like radiation and gravitational effects. I explored modifying communication features and using solar radiation for better prediction techniques [3], [4]. I also examined TCP Congestion Control and Deep Reinforcement Learning to improve data transmission strategies [5] and explored the importance of CCDS File Delivery Protocols (CFDP) for reliable file transfers in deep space [6], [7].

Recent studies integrating AI and ML into satellite communication systems [8], [9] highlight challenges and opportunities for onboard processing and neural network applications in massive satellite networks. These studies emphasize how AI mitigates rapid elevation angle changes and predicts channel variations, stressing the importance of neural networks in advancing space exploration forecasting.

IV. Methodology

A. Database Used

The NOAA DSCOVR satellite, located at Lagrange Point 1 (L1), continuously monitors solar wind parameters and magnetic field variations using the PlasMag suite. Key instruments include:

- **Fluxgate Magnetometer (MAG)**: Measures magnetic field variations to assess disruptions to Earth's magnetosphere.
- **Faraday Cup (FC)**: Provides solar wind characteristics, including speed, density, and temperature [1].

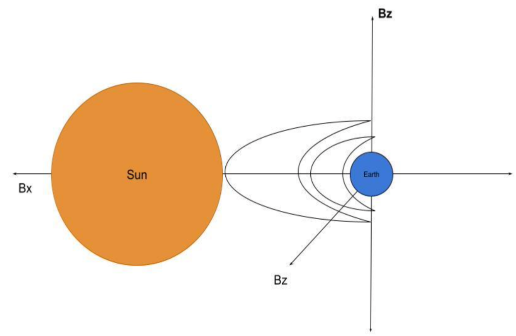

Fig. 1. Monitoring the Bz value.

B. Pre-Processing

Figure 4 pictures the Bz value calculation.

The NOAA dataset is processed as follows:

1) Unnecessary columns are removed to simplify inputs.
2) Data is categorized based on the Bz component of the interplanetary magnetic field (IMF):
   - Severe storms: $Bz < -50$ nT
   - Strong storms: $-50 \leq Bz < -20$ nT
   - Moderate storms: $-20 \leq Bz < -10$ nT
   - No storm: $Bz \geq -10$ nT
3) Features are normalized using MinMaxScaler to ensure balanced model training.

The proposed model takes account of the relationships that the solar wind's speed, density, and temperature have with the Earth's magnetic field to estimate future metrics of solar wind. It works with input data that is organized as (time_steps, features), where "features" represent the data points at each step, and "time_steps" indicate the length of the sequence. This structure is designed to include important factors like elevation angle, attenuation of rain, and other noteworthy atmospheric conditions, guaranteeing a thorough approach to forecasting. My neural network architecture includes two LSTM layers that capture both short-term and long-term dependencies in the data. To avoid overfitting, a common challenge with complex models, I integrate dropout layers. Within the network's final layer is a dense layer, meaning all layers are fully connected, optimized for making continuous value predictions essential for the predictions. The optimizer used is 'Standard Gradient Descent,' which helps to speed up the learning process for the model. Finally, the loss function used is mean squared error, which is commonly used within regression models.

The 'basic_nn' function shown Figure 2, defines a simple feedforward neural network model used for regression tasks, specifically to predict continuous values such as the intensity of geomagnetic storms based on input data. The model consists of three layers: the first layer has 64 neurons with a ReLU activation function, the second layer has 32 neurons with ReLU activation, and the final layer contains a single neuron to output the predicted value. The model is compiled with the Adam

```python
def basic_nn(input_size, lr):
    model = Sequential([
        Dense(64, input_dim=input_size, activation='relu'),
        Dense(32, activation='relu'),
        Dense(1)
    ])

    optimizer = Adam(learning_rate=lr)
    model.compile(optimizer=optimizer, loss='mean_squared_error',
                  metrics=['mean_absolute_error','accuracy'])

    return model
```

Fig. 2. Neural network function used.

optimizer, which adjusts the learning rate during training, and the mean squared error (MSE) loss function, which minimizes the difference between predicted and actual values. Additional metrics, including mean absolute error (MAE) and accuracy, are tracked during training. This function provides a basic structure for the neural network, making it suitable for simpler prediction tasks, though for more complex relationships like those found in space weather forecasting, more advanced architectures such as recurrent neural networks (RNNs) or LSTM models may be more appropriate for capturing temporal dependencies. The source code for the basic_nn model, along with other related neural network architectures, can be found in my GitHub repository [10]

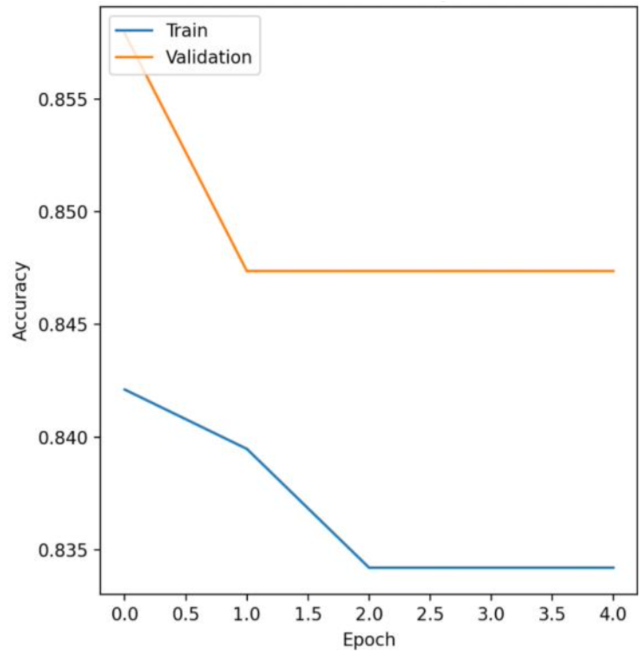

Fig. 3. Model Accuracy

V. Results

A. Training and Validation

The model achieves 83% to 84% accuracy over four epochs, with consistent validation accuracy. Training loss decreases significantly, while validation loss shows minimal increases, indicating effective generalization. As seen in Figure 1, the accuracy for 4 Epochs ranges from 83% to 84%, with validation accuracy being much higher. This training accuracy measures the model's ability to forecast geomagnetic storms based on the training dataset, indicating successful learning when there is an increasing trend. Validation accuracy, representing the model's performance on a different dataset not seen during training, is essential for assessing its generalization abilities. A high and consistent validation accuracy indicates effective performance on untrained data. However, if training accuracy increases while validation accuracy declines, it is likely suggesting that over-fitting is occurring, where the model learns noise and outliers that do not reflect true geomagnetic patterns. Training loss, shown in Figure 2, decreases as a sign that the model's predictions are becoming more accurate. An increase in validation loss, despite a decreasing training loss, may once again be indicating over-fitting. However overall, the loss is very small before the signs of over-fitting begin to show, meaning that the model has performed quite well.

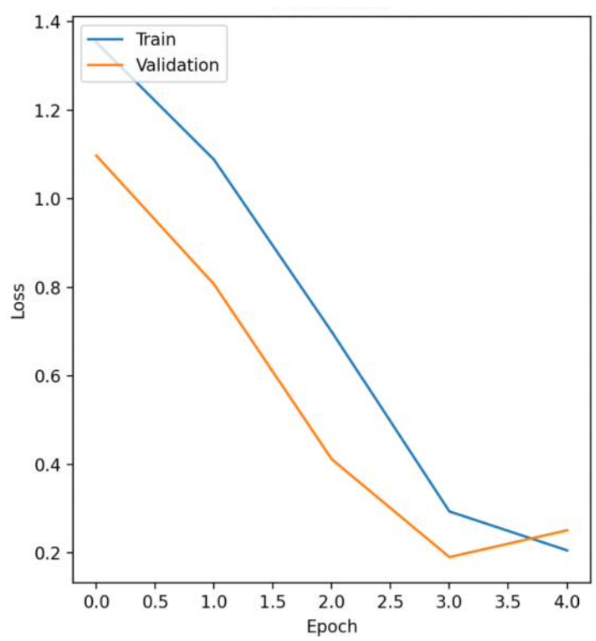

Fig. 4. Model Loss.

B. Overfitting Mitigation

Regularization techniques, including L1 and L2 penalties, are used to reduce overfitting and focus the model on significant patterns. Future iterations explore adding new features and datasets to improve robustness.

VI. Conclusion and Future Work

This research demonstrates the feasibility of using LSTM neural networks to predict geomagnetic storms using solar wind data. Future work will focus on:

- Expands the model with additional variables and datasets.
- Explores alternative neural network architectures.
- Develops a real-time predictive system for operational use in space weather monitoring.

Acknowledgments

The author acknowledges NOAA for providing DSCOVR satellite data and all collaborators for their support.

References

[1] J. Foust, "Geomagnetic storms cause 'mass migrations' of satellites," spacenews," *SpaceNews*, 2024. [Online]. Available: https://spacenews.com/geomagnetic-storms-cause-mass-migrations-of-satellites/#:~:text=WASHINGTON%20%20A%20pair%20of%20major,concerns%20about%20space%20traffic%20coordination.

[2] R. Horne, S. Glauert, N. Meredith, D. Boscher, V. Maget, D. Heynderickx, and D. Pitchford, "Space weather impacts on satellites and forecasting the earth's electron radiation belts with spacecast," *Space weather*, vol. 11, no. 4, pp. 169–186, 2013.

[3] V. U. Nwankwo, N. N. Jibiri, and M. T. Kio, "The impact of space radiation environment on satellites operation in near-earth space," in *Satellites Missions and Technologies for Geosciences*, V. Demyanov and J. Becedas, Eds. Rijeka: IntechOpen, 2020, ch. 5. [Online]. Available: https://doi.org/10.5772/intechopen.90115

[4] D. Liu, Y. Cui, Z. Feng, and Y. Wang, "Analysis and application of deep space exploration satellite telemetry data combined with empirical mode decomposition and arima model," *Journal of Physics: Conference Series*, vol. 2489, no. 1, p. 012045, may 2023. [Online]. Available: https://dx.doi.org/10.1088/1742-6596/2489/1/012045

[5] T. Ha, A. Masood, W. Na, and S. Cho, "Intelligent multi-path tcp congestion control for video streaming in internet of deep space things communication," *ICT Express*, vol. 9, no. 5, pp. 860–868, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405959523000231

[6] S. Pavale, U. E, and P. Laksminarasimhan, "Design, implementation and performance evaluation of ccsds cfdp protocol," *2010 IEEE International Conference on Computational Intelligence and Computing Research*, pp. 1–4, 2010. [Online]. Available: https://api.semanticscholar.org/CorpusID:18989915

[7] F. A. Sanders, G. Jones, and M. Levesque, "Transfer of files between the deep impact spacecrafts and the ground data system using cfdp: a case study," in *2007 IEEE Aerospace Conference*. IEEE, March 2007, pp. 1–5.

[8] P. V. R. Ferreira, R. Paffenroth, A. M. Wyglinski, T. M. Hackett, S. G. Bilen, R. C. Reinhart, and D. J. Mortensen, "Reinforcement learning for satellite communications: From leo to deep space operations," *IEEE Communications Magazine*, vol. 57, no. 5, pp. 70–75, 2019.

[9] F. Ortíz, V. M. Baeza, L. M. Garcés-Socarrás, J. A. Vásquez-Peralvo, J. L. Gonzalez, G. Fontanesi, E. Lagunas, J. Querol, and S. Chatzinotas, "Onboard processing in satellite communications using ai accelerators," *Aerospace*, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:256159368

[10] M. Siddiqui, "Honours thesis: Geomagnetic prediction model," 2025. [Online]. Available: https://github.com/manalsiddiqui/honours-thesis-geomagnetic-prediction-model