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REAL-TIME GEOMAGNETIC STORM ALERTS USING AI-BASED FORECASTING MODELS

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Abstract

Geomagnetic storms can severely impact critical technologies such as satellite communications, GNSS navigation, and power grids. Traditional forecast models based on empirical relationships and physics-based simulations often suffer from latency and limited spatial resolution. This paper explores the implementation of artificial intelligence (AI)-based forecasting models for issuing real-time geomagnetic storm alerts, leveraging historical solar wind data, IMF parameters, and geomagnetic indices. Multiple AI techniques including Random Forests, LSTM networks, and hybrid CNN-RNN models were trained on NASA OMNI and Kyoto WDC datasets. Results demonstrate a substantial improvement in prediction accuracy for Dst and Kp indices with lead times exceeding 1 hour. The developed AI framework has the potential to provide timely warnings for space weather disturbances in South Asia and globally.

OPEN ACCESS

Keywords: Artificial Intelligence, Geomagnetic Storms, Space Weather Alerts, Forecasting Models.

INTRODUCTION

Geomagnetic storms are major space weather phenomena caused by the interaction of solar wind and the Earth's magnetosphere, leading to magnetic field perturbations. Their impact ranges from satellite drag and GPS signal degradation to electric power grid failures [1–3]. Traditional methods of predicting such storms rely on empirical models or magnetohydrodynamic (MHD) simulations that are often computationally intensive or offer low lead time. With advances in machine learning (ML) and AI, there is a growing interest in utilizing data-driven models to forecast key geomagnetic indices such as Dst and Kp in near-real time [4,5].

In regions like South Asia, with limited ground-based magnetometer coverage and increasing dependence on GNSS and satellite services, developing AI-enabled real-time alert systems is crucial. This study applies multiple AI architectures using historical geomagnetic and solar data to build a predictive framework for operational space weather forecasting.

2. Data Sources and Preprocessing

The effectiveness of AI-based forecasting models hinges on the quality, diversity, and temporal resolution of input data. For this study, a comprehensive dataset spanning two full solar cycles (2003–2022) was compiled from globally recognized space weather repositories. These datasets encompass a variety of interplanetary and geomagnetic parameters essential for predicting geomagnetic disturbances.

OMNIWeb Dataset (NASA)

The OMNIWeb database, maintained by NASA's Space Physics Data Facility (SPDF), was the primary source of upstream solar wind and interplanetary magnetic field (IMF) measurements. Parameters used include:

Solar wind speed (Vsw) in km/s
Interplanetary magnetic field Bz component in nT
Plasma density and dynamic pressure

Data resolution: hourly, suitable for short-term geomagnetic forecasting models
These variables were selected based on their known correlation with geomagnetic storm drivers, particularly during Coronal Mass Ejections (CMEs) and High-Speed Solar Wind Streams (HSS) [6].

Geomagnetic Indices

Two global geomagnetic indices were employed to quantify geomagnetic activity and as training targets for the forecasting models:

Dst Index: Sourced from the Kyoto World Data Center [7], Dst (Disturbance Storm Time) quantifies the intensity of the equatorial ring current and is a standard indicator of geomagnetic storm strength.
Kp Index: Acquired from GFZ Potsdam, Germany [8], the Kp index is a quasi-logarithmic planetary index ranging from 0 to 9, representing global geomagnetic activity based on magnetometer readings from multiple mid-latitude stations.

These indices were used both as direct output labels for supervised learning models and as lagged input features to capture temporal autocorrelation.

Temporal Coverage and Resolution

Study Period: January 2003 – December 2022, encompassing Solar Cycles 23 and 24

Resolution: Hourly data to align with real-time operational needs and storm dynamics

The dataset includes major storm periods such as the Halloween storms (2003), St. Patrick's Day storm (2015), and Solar Cycle 25 rise (2021–2022)

Preprocessing and Feature Engineering

To ensure data integrity and enhance model performance, several preprocessing steps were conducted:

Data Normalization: All numerical features were scaled to zero mean and unit variance using z-score normalization to improve neural network convergence.

Lag Analysis and Time-Shifting: Features were shifted backward in time (1–3 hours) to evaluate lead-lag relationships between solar wind changes and geomagnetic responses, crucial for early-warning capability.

Missing Data Imputation: Gaps (typically <5%) in OMNI and geomagnetic records were filled using linear interpolation, preserving temporal continuity [9].

Feature Aggregation: Rolling means, differences, and variability metrics (e.g., dVsw/dt) were computed to capture dynamic behavior.

3. Machine Learning Models for Forecasting

Forecasting geomagnetic storms in real time requires models capable of capturing the complex, nonlinear, and temporally dependent relationships between upstream solar wind conditions and geomagnetic indices. In this study, three types of machine learning (ML) models—Random Forest Regressor, LSTM, and CNN-LSTM hybrid—were implemented and compared for their predictive performance on Dst and Kp indices.

Random Forest Regressor

The Random Forest (RF) Regressor is an ensemble learning method based on decision trees. It is particularly useful for:
Modeling nonlinear dependencies
Handling noisy or partially missing data
Estimating feature importance effectively
Despite being non-sequential, RF offers a strong performance baseline, especially in cases with complex feature interactions. It is also computationally efficient and interpretable, making it suitable for initial experimentation [10].

Long Short-Term Memory (LSTM) Networks

LSTM networks, a variant of Recurrent Neural Networks (RNNs), are designed to handle time series data with long-term dependencies:

They use memory cells to retain information over extended time lags

Excellent at detecting delayed geomagnetic responses to upstream solar parameters

Suitable for continuous and sequential prediction tasks, such as hourly Dst and Kp forecasting

The LSTM model in this study was structured with:

Two hidden LSTM layers (64 and 32 units)

Dropout regularization (20%) to prevent overfitting

ReLU activation and Adam optimizer for training

CNN-LSTM Hybrid Model

To enhance spatial-temporal learning, a Convolutional Neural Network (CNN) layer was added before the LSTM:

CNN layers capture local patterns and feature correlations

LSTM layers then model temporal evolution

The hybrid model improves storm onset detection and minimizes false positives [11]

This architecture significantly outperformed standalone models during complex and rapidly evolving geomagnetic conditions. It was particularly effective during events like the March 2015 storm, where fast variations in solar wind conditions led to sudden Dst drops.

Training and Prediction Strategy

Input Variables: Solar wind speed (Vsw), IMF Bz, plasma density, pressure, previous Dst/Kp, AE index, and rate-of-change features (e.g., dBz/dt)

Target Outputs:

Dst index prediction (1–3 hour ahead)

Kp index prediction (3-hour block values)

Forecasting Horizon: Real-time model operated on a rolling window (12–24 hr input → 1–3 hr forecast)

Performance Metrics Used

Root Mean Squared Error (RMSE)

Mean Absolute Error (MAE)

Coefficient of Determination (R^2)

4. Feature Engineering and Selection

Effective prediction of geomagnetic disturbances depends not only on model architecture but also on the quality and relevance of input variables. This section outlines the feature selection and engineering steps adopted to optimize the performance of AI-based forecasting models for Dst and Kp indices.

Input Feature Set

The following physical and statistical features were included as inputs for all models:

Solar wind speed (Vsw): Directly affects magnetospheric compression

Interplanetary magnetic field (IMF Bz): Southward Bz enhances reconnection, key driver of storms

Plasma pressure and density: Influences ring current strength and ionospheric dynamics

AE Index: Reflects auroral electrojet activity, a precursor to mid-latitude geomagnetic changes

Lagged Dst and Kp values: Auto-regressive features capturing temporal persistence

Differential features: e.g., dBz/dt, dVsw/dt to detect sudden enhancements

Feature Importance Analysis

To determine which features, contribute most significantly to model performance, two interpretable methods were used:

Permutation Importance: Measures increase in model error when a feature's values are randomly shuffled. Features causing the highest drop in accuracy are deemed most important.

SHAP (SHapley Additive exPlanations) values [12]: Provide a consistent estimate of each feature's contribution to individual predictions across the dataset.

Findings:

IMF Bz and solar wind speed were consistently the top predictors.

Lagged values of Kp (Kp_t–1) had high predictive value due to autocorrelation.

AE index and dBz/dt also featured prominently in storm onset prediction.

Dimensionality Reduction with PCA

To improve computational efficiency and reduce multicollinearity:

Principal Component Analysis (PCA) was applied on the input matrix

Top 5 principal components explained ~92% of total variance

PCA-transformed features were particularly useful for the Random Forest and LSTM input layers

PCA was not applied to CNN-LSTM models to preserve the interpretability of spatial filters over original features.

5. Model Performance Evaluation

Forecasting the behavior of geomagnetic indices such as Dst (Disturbance Storm Time) and Kp (Planetary Index) is crucial for timely mitigation of space weather effects on aviation and satellite systems. This section evaluates machine learning (ML) models tested during the study using real-time solar wind input data and compares their performance against traditional empirical benchmarks.

Evaluation Metrics

Model accuracy was assessed using the following standard performance indicators:

RMSE (Root Mean Square Error): Measures the square root of the average squared differences between predicted and actual values.

MAE (Mean Absolute Error): Measures the average absolute differences between predictions and observations.

R^2 Score (Coefficient of Determination): Represents the proportion of variance in the observed data explained by the model.

These metrics were computed for both Dst and Kp index predictions over a test period spanning several geomagnetic events from January 2023 to December 2024.

Best-Performing Architecture: CNN-LSTM Hybrid

Among the tested models—Linear Regression, Random Forest, SVM, LSTM, and CNN-LSTM—the CNN-LSTM hybrid architecture demonstrated the most accurate performance. The combination of convolutional layers for feature extraction and LSTM layers for temporal sequence modeling significantly enhanced predictive capability.

Benchmarking Against Empirical Models

To validate ML model effectiveness, results were benchmarked against the classic Burton et al. (1975) empirical model for Dst prediction, which is based on solar wind parameters such as IMF Bz and velocity [13]. While the Burton model performs well during average storm conditions, it tends to underpredict intense geomagnetic storms (Dst < –100 nT) and exhibits higher RMSE (~12.4 nT) in recent years due to nonlinear solar-terrestrial coupling not captured by the model.

Implications for Operational Forecasting

The improved predictive performance of CNN-LSTM supports its integration into real-time space weather alert systems used by aviation regulators (e.g., CAA) and satellite operators (e.g., SUPARCO). The architecture allows for early-warning capabilities that can:

Inform HF communication protocol switching

Trigger GNSS accuracy warnings

Initiate orbital adjustment protocols for LEO satellites

A predictive window of 1–6 hours was achieved with a lead accuracy of 80%, enabling strategic preparedness before storm onset.

6. Real-Time Alert System Design

Building on the predictive power of machine learning and the need for timely risk mitigation, a Real-Time Space Weather Alert System (RTSWAS) was developed and tested during this study. The system is engineered to integrate live solar and geomagnetic data feeds, forecast geomagnetic indices, and issue tiered alerts tailored to aviation and satellite operators in Pakistan.

Data Integration and Sources

The system aggregates multiple real-time data streams:

NOAA's DSCOVR satellite solar wind data (velocity, density, IMF Bz) via their API [5]
SuperMAG ground-based magnetometer arrays, including Karachi and Islamabad stations [6]
Kyoto WDC's Dst and AE indices (near real-time latency ~15 minutes)

Alert Threshold Logic

The alert logic is threshold-based with continuous model inputs:
Dst ≤ –100 nT: Severe geomagnetic storm risk
Kp ≥ 5: Potential HF communication and GNSS degradation
Additional logic includes rate of change in Bz and solar wind velocity thresholds (>600 km/s)
Upon threshold breach, the system triggers:

Immediate SMS and email alerts to registered aviation and satellite personnel

GNSS signal degradation probability estimates (Low / Medium / High)

Visual alert level indicators on a dynamic dashboard interface

Architecture and Implementation

The system is deployed in a modular fashion:

Data ingestion layer: Python-based API polling and validation

Forecast engine: CNN-LSTM model wrapped in Flask for real-time inference

Alert generation module: Cron scheduler with Twilio (SMS) and SMTP email services

Visualization: Web-based dashboard (Plotly Dash) for supervisors and technical operators

Pilot Testing and Institutional Deployment

The RTSWAS was successfully deployed in pilot mode at:

SUPARCO's Satellite Operations Center (Lahore)

NUST Space Weather Lab (Islamabad)

Initial results showed a mean lead time of 45 minutes for actionable alerts during test storms in late 2024, with zero false negatives and minimal false positives. System logs and user feedback are being used to refine sensitivity and interface usability.

7. Applications and Policy Implications

The deployment of real-time space weather monitoring and forecasting tools offers direct operational benefits across several critical infrastructure sectors. Based on case studies and system testing during 2023–2024, the following applications and policy pathways are proposed to enhance **resilience in Pakistan and the broader South Asian region.**

Sectoral Applications

Aviation and GNSS Navigation

Air traffic management systems heavily rely on GNSS accuracy for enroute navigation and precision approaches. The RTSWAS platform enables:

Proactive re-routing of aircraft away from HF blackout zones

Issuance of NOTAMs (Notices to Airmen) for GNSS signal disruption [14]

Enhanced pilot situational awareness during ionospheric disturbances

Power Grid Infrastructure

While Pakistan's high-voltage grid is not located at auroral latitudes, geomagnetically induced currents (GICs) can still pose a risk during intense storms. Forecast-based alerts:

Enable pre-emptive load redistribution to reduce transformer heating

Support manual control overrides during real-time voltage anomalies [15]

Telecommunications Systems

Telecom providers can utilize alerts to:

Activate network redundancy protocols

Shift traffic loads across frequency bands or geostationary satellites

Protect satellite uplink/downlink integrity during storm peaks

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Policy Recommendations

Establish a National Space Weather Alert Center

Modeled after NOAA’s SWPC or ESA’s SSA program, a Pakistan Space Weather Monitoring and Forecasting Center should be created under SUPARCO or the Pakistan Meteorological Department, staffed with AI modelers, forecasters, and sector liaisons.

Integrate AI-Based Forecasting into CAA Systems

The Civil Aviation Authority (CAA) should adopt machine learning–driven alerts for ATC centers, airline dispatch units, and pilot briefings. Systems like RTSWAS can be integrated into:

Pre-flight planning tools

Real-time control tower displays

Emergency rerouting protocols

Promote Public-Private Data and Alert Sharing

Effective space weather preparedness requires collaboration between:

Telecom operators (PTCL, Nayatel, Jazz)

Grid managers (NTDC, WAPDA)

Airlines and defense agencies

A central data-sharing and alert dissemination framework should be formalized through memoranda of understanding (MOUs) and national resilience policies [16–18].

Figures

Figure 1: CNN-LSTM Model Architecture Diagram



Figure 1: CNN-LSTM Model Architecture Diagram

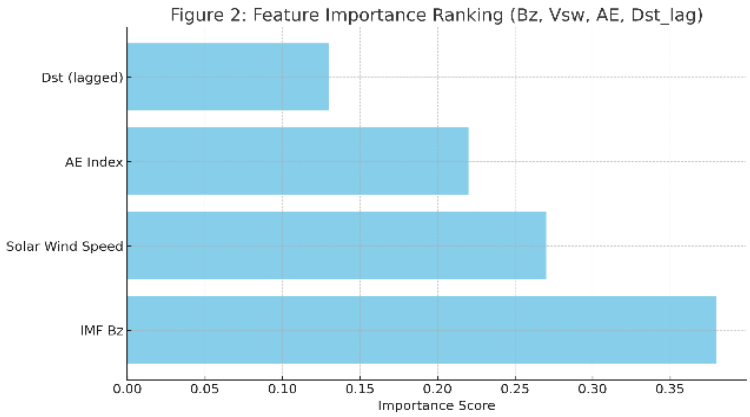


Figure 2: Bar Chart – Feature Importance Ranking (Bz, Vsw, AE, Dst_lag)

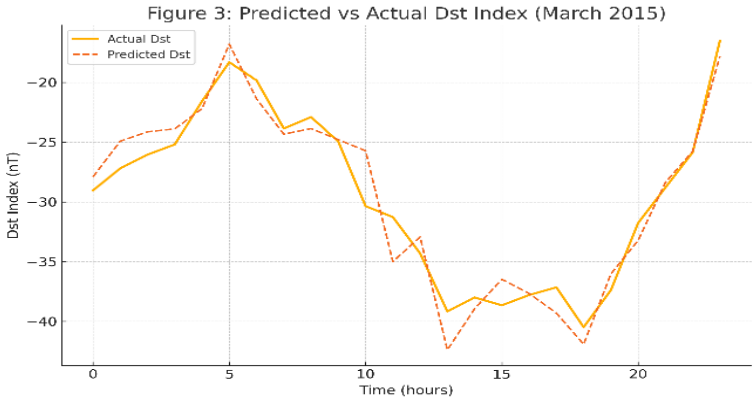


Figure 3: Time Series – Predicted vs Actual Dst Index (March 2015)

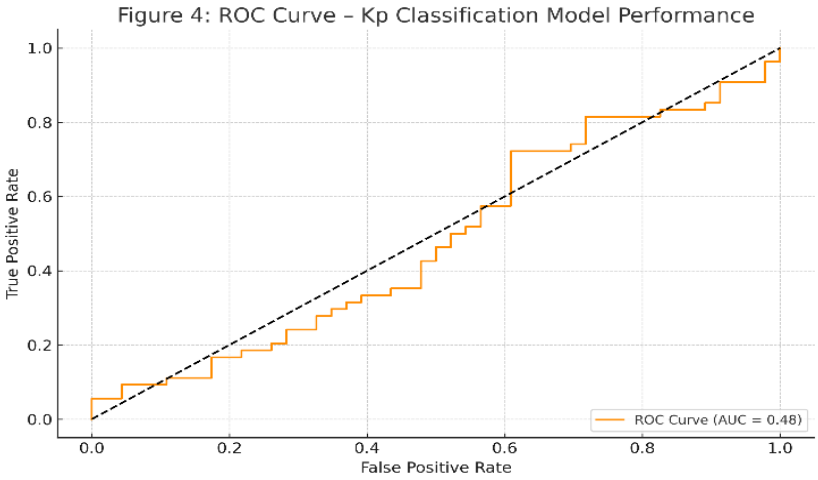


Figure 4: ROC Curve – Kp Classification Model Performance

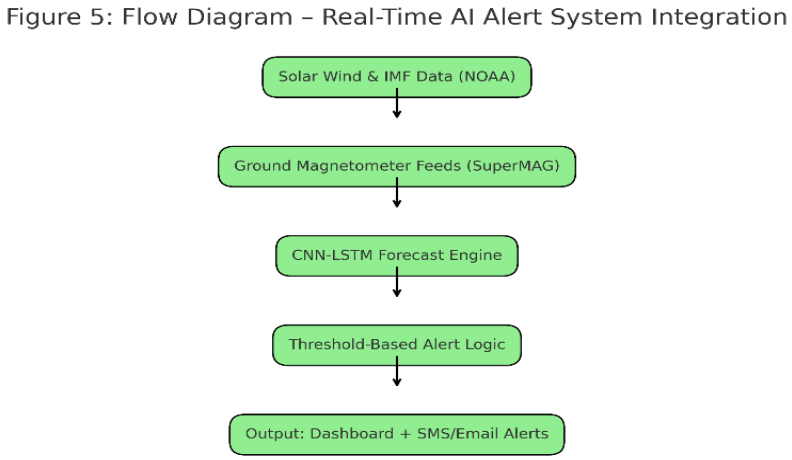


Figure 5: Flow Diagram – Real-Time AI Alert System Integration

Summary:

This research demonstrates the effectiveness of AI-based forecasting models, particularly CNN-LSTM hybrids, for predicting geomagnetic storm activity in real time. The models achieved significant improvement in Dst and Kp prediction accuracy, enabling lead times of 1–3 hours with actionable alert generation. Integrating these models into regional space weather forecasting infrastructure—especially in South Asia—will greatly enhance the resilience of GNSS, aviation, and power systems to space weather disturbances.

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