



Problem Statement and Team Details



Problem Statement: Space Weather Monitoring & Solar Storm Risk Predictor
Develop a model that forecasts geomagnetic storms and solar flare impact on satellites and communication systems.

Team Name: Sol-Ark

Team Leader Name: AVINASH

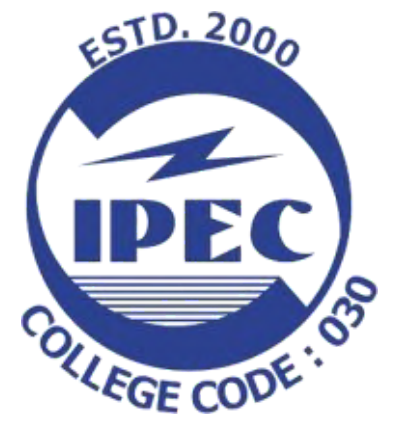
Institute Name: G.L. Bajaj Institute of Technology and Management, Greater Noida

Members Name: Avinash, Mahwish Ali Naaz, Tanisha Chauhan,
Prakhar Saxena and Kaustubh Kant Rastogi





Problem and Solution



Problem Statement:

Solar storms and geomagnetic disturbances can severely affect satellites, GPS, communication networks, aviation systems, and power grids.

However, the lack of reliable and timely prediction mechanisms makes it difficult to anticipate these events and reduce their impact. With increasing dependence on space-based technology, effective space weather monitoring has become a critical challenge.

Solution:

An AI-driven space weather monitor that:

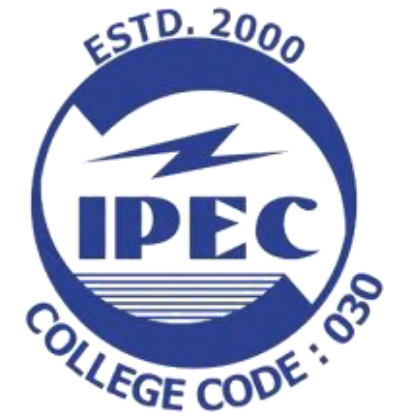
- Tracks solar activity in real time
- Predicts storm severity before it reaches Earth
- Assesses the risk to satellites and communication networks
- Sends early alerts, giving operators time to act and protect systems





Methodology & Implementation

Journey to Innovation



[Sol-Ark Website](#)

| Stage | Methodology | Implementation |
|----------------------|---|--|
| Overview | <ul style="list-style-type: none">Collected historical space-weather data from NASA OMNI & NOAA.Identified key geomagnetic storm drivers.Trained and evaluated multiple ML models.Selected best model for real-time forecasting. | <ul style="list-style-type: none">End-to-end ML forecasting system.Backend: Python ML pipeline.Frontend: React-based dashboard.Live data ingestion from NOAA (DSCOVR). |
| Data Collection | <ul style="list-style-type: none">Historical solar wind & geomagnetic data (2018–2024).<ul style="list-style-type: none">Solar Wind Speed (V)Proton Density (Np)IMF Field (Bz, Bt)Kp Index (Target) | <ul style="list-style-type: none">Data cleaning & alignmentFeature engineeringModel training & evaluationTrained model saved for inference |
| Feature Engineering | <ul style="list-style-type: none">Time-lag FeaturesRolling Averages$E_y = V \times [B_z]$ | <ul style="list-style-type: none">Fetch live solar wind dataPreprocess & feature extractionRun XGBoost Model |
| Modeling & Selection | <ul style="list-style-type: none">Trained ML Models:<ul style="list-style-type: none">Random ForestXGBoostBest Model: XGBoostMAE \approx 0.51R² = 0.75 | <ul style="list-style-type: none">Predicted Kp IndexStorm Risk Levels:<ul style="list-style-type: none">Low Moderate SevereInteractive Dashboard |

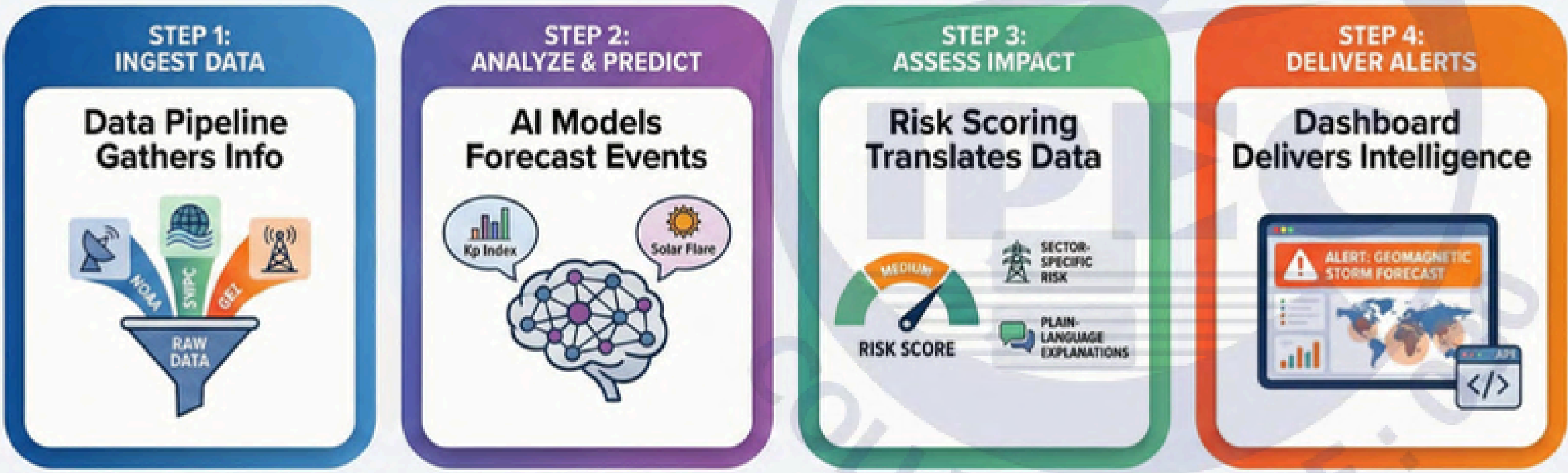
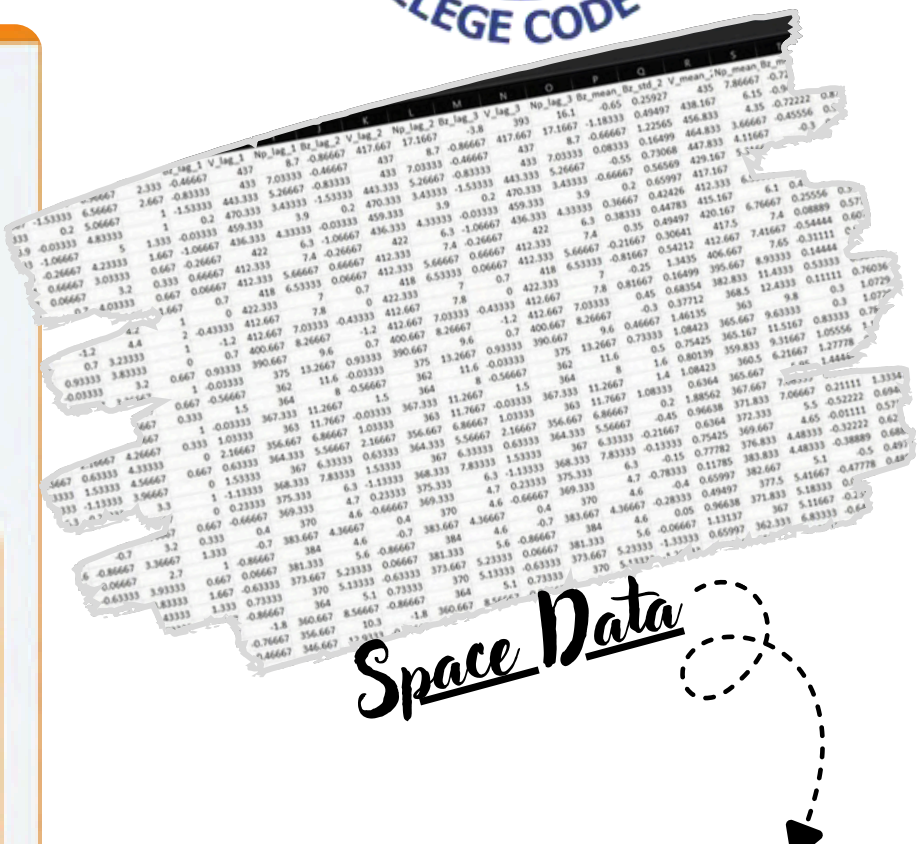
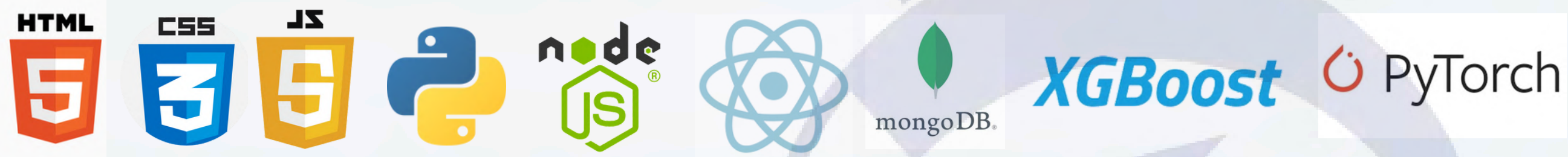


GitHub

[Sol-Ark Repo](#)



TECHNOLOGY USED



Fetches near-real-time data from open sources like NOAA, SWPC, and GFZ.

Two core models (Kp Index & Solar Flare) are trained on historical data to predict geomagnetic storms and flares.

Converts complex model outputs into sector-specific risk scores and plain-language explanations.

A web dashboard and API provide users with real-time monitoring, alerts, and forecasts.

```
from sklearn.ensemble import RandomForestRegressor
rf_model = RandomForestRegressor(
    n_estimators=200,
    max_depth=15,
    random_state=42,
    n_jobs=-1
)
rf_model.fit(X_train, y_train)
rf_preds = rf_model.predict(X_test)
rf_metrics = evaluate_model(y_test, rf_preds)

from xgboost import XGBRegressor
xgb_model = XGBRegressor(
    n_estimators=300,
    learning_rate=0.05,
    max_depth=6,
    subsample=0.8,
    colsample_bytree=0.8,
    random_state=42,
    objective="reg:squarederror"
)
xgb_model.fit(X_train, y_train)
xgb_preds = xgb_model.predict(X_test)
xgb_metrics = evaluate_model(y_test, xgb_preds)
```

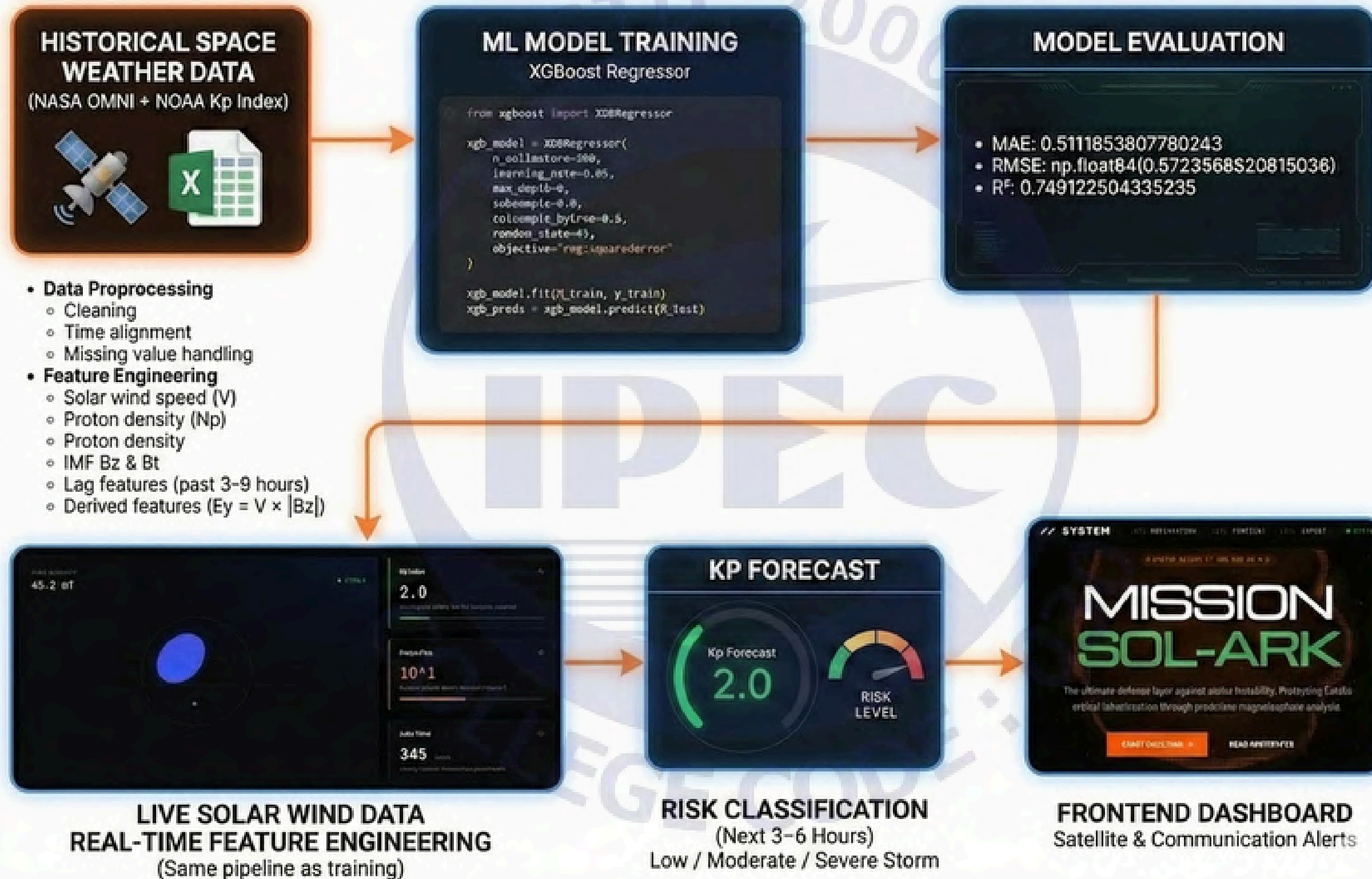
{ 'MAE': 0.5207743448478116, 'RMSE': np.float64(0.68649960376), 'R2': 0.7384572913292348 }

{ 'MAE': 0.5111653807780243, 'RMSE': np.float64(0.6723568520815036), 'R2': 0.749122504335235 }

AI Model Training



Flowchart & Supporting Images



.....AND MANY MORE UPCOMING EVOLUTIONS IN PROGRESS.



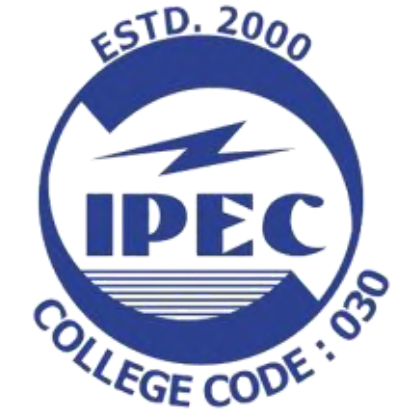
Metaverse
3D Tour



Bio-Resistant
Suit



Aurora
Virtual & AR



Feasibility and Market Use

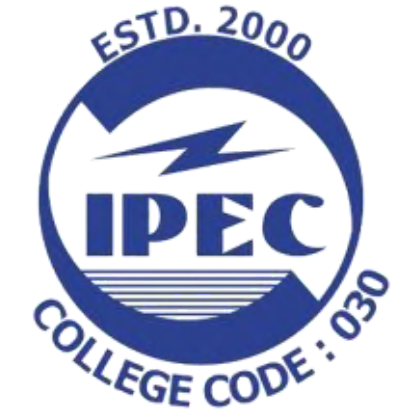
Feasibility

- Data availability: from NASA, NOAA, and other space agencies in easy and imagined form of charts.
- Can be deployed as a web dashboard or API for satellite operators
- Cost-effective compared to the potential damage from unpredicted solar storms.
- Automatic updates and notifications ensure minimal manual intervention
- Integration: Can be connected with satellite control systems

Market Use

Potential Customers

- Satellite operators
(SpaceX, ISRO, NASA, OneWeb)
- Telecom companies using satellites
(VSAT, GPS)
- Aviation & airlines
(flight safety)
- Power/grid operators
(storm impact on lines)
- Research & government agencies
(NOAA, ISRO, NASA, DRDO)



Conclusion

Our AI-powered Space Weather monitoring system enables safer and smarter use of space technology.

**Predict
geomagnetic
storm risks before
damage occurs**

**Supports space
agencies,
telecoms, and
power grids**

REFERENCES

<https://www.swpc.noaa.gov/products/planetary-k-index>

<https://agupubs.onlinelibrary.wiley.com/>

<https://www.isro.gov.in/search.html#gs.c.q=Space%20Storm>

**Ready for real-
world deployment
and future
expansion.**

**Reduces
operational risk
for satellites and
communication
systems**