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BHARATIYA ANTARIKSH HACKATHON 2025

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Team Name : Interstellar

Team Leader Name : Amey Taksali

Problem Statement : Identifying halo CME events based on particle data from SWIS-ASPEX payload onboard Aditya-L1

Team Members

Team Leader:

Name: Amey Taksali
College: Indian Institute of Technology Guwahati

Team Member-1:

Name: Ridhima Gupta
College: Indian Institute of Technology Guwahati

Team Member-2:

Name: Nihira Patwardhan
College: Indian Institute of Technology Guwahati

Brief about the Idea:

Our system detects CME shocks before they strike , using only onboard particle and magnetic field data from Aditya-L1's ASPEX payload. It’s fast, physics-grounded, and works in real time without needing coronagraphs or lagging Earth-based indicators.

FEATURE 1 – PREDICTIVE PARTICLE SPIKE WARNING:

- **Goal**: Provide earliest warning of incoming CME shocks.
- **How**: Learns dynamic SEP (Solar Energetic Particles) flux baseline → flags sustained anomalies.
- **Unique:** Uses cross-entropy divergence to check physical plausibility (not just spikes).

FEATURE 2– REAL TIME SHOCK DETECTION:

- **Goal**: Confirm if anomaly is a true CME.
- **How**: CNN-LSTM-Attention trained only on RH-confirmed shocks.
- **Output**: PVSS — a physics-grounded shock score with uncertainty confidence.

How different is it from any of the other existing ideas?

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Unlike conventional approaches that depend heavily on coronagraph imagery or lagging near-Earth indicators, our solution **uses particle and magnetic field** data from the SWIS instrument aboard Aditya-L1 to identify halo CME signatures with a strong foundation in solar wind physics.

USPs OF OUR PROPOSED SOLUTION

Physics-Based CME Detection
Uses magnetic, plasma & particle data with RH checks and Mahalanobis scoring

Temporal Pattern Learning
CNN-LSTM-Attention captures CME evolution across time sequences.

Trustable Alerts
MC Dropout gives prediction confidence with uncertainty bounds.

Directional Spike Detection
Cross-entropy spots beam-like flux from halo CMEs.

List of features offered by the solution :-

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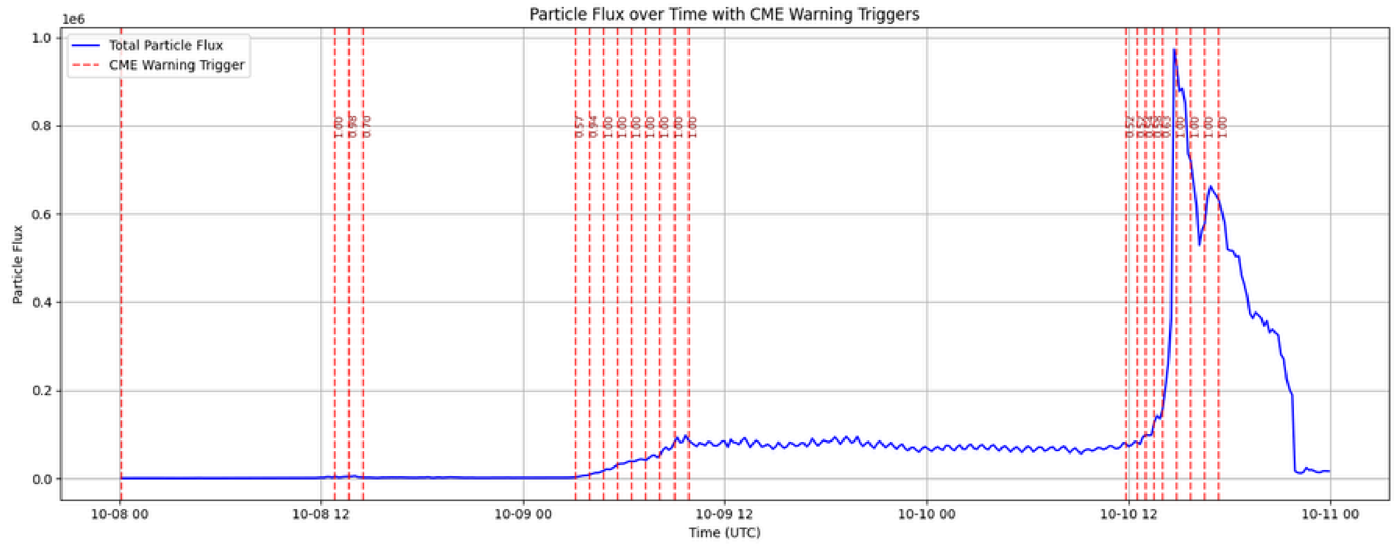
Feature 1 :- Predictive Particle Spike Warning

Feature	What It Does
Dynamic Flux Detection	• Adapts to background using a 12-hour rolling IQR baseline no static thresholds. • Computes confidence based on anomaly strength.
High-Energy Weighting	• Prioritizes extreme events over low-energy background.
Cross-Entropy Directionality	• Uses Cross-Entropy Divergence between inner and outer bins inspired by Kullback–Leibler (KL) Divergence
Adaptive Thresholding	• Dynamically adjusts alert sensitivity based on background noise.
Physics-Based Cooldown	• Prevents alert spam by scaling reset time with event length.

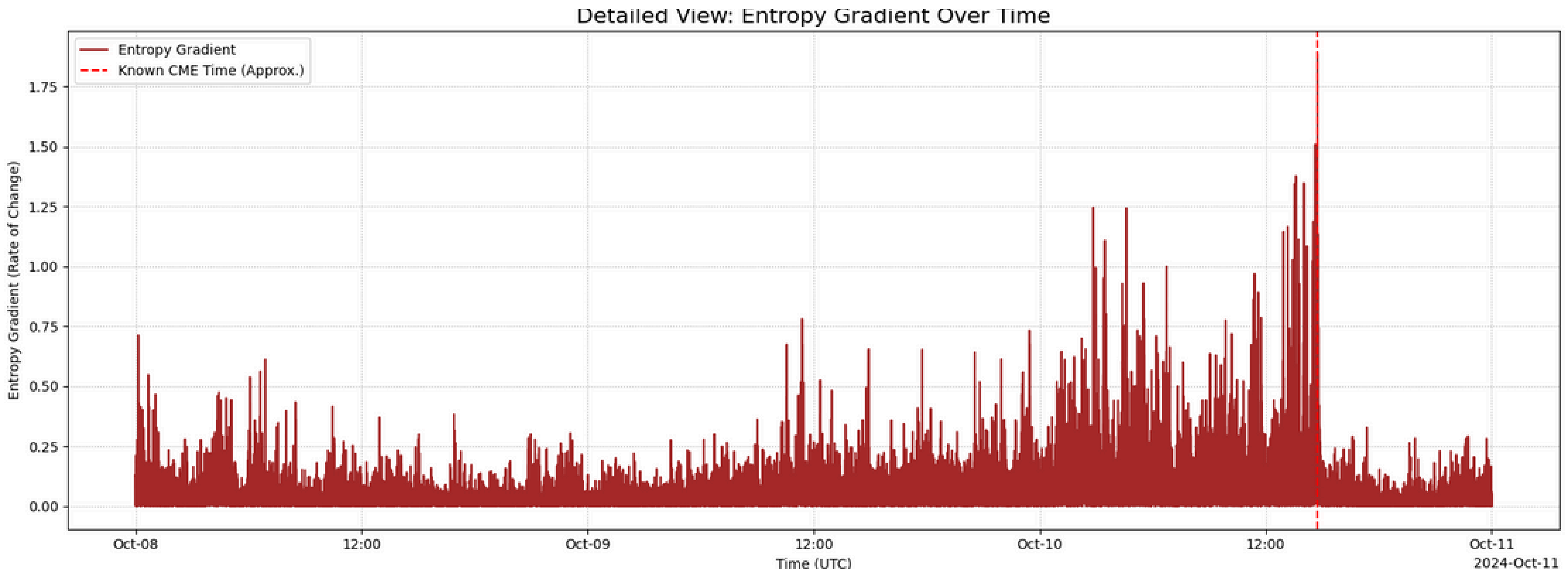


Red dotted warning issued by model are plotted with particle flux detected

DATA USED: SWIS + STEPS

Feature 2 :- Real-Time Shock Detection

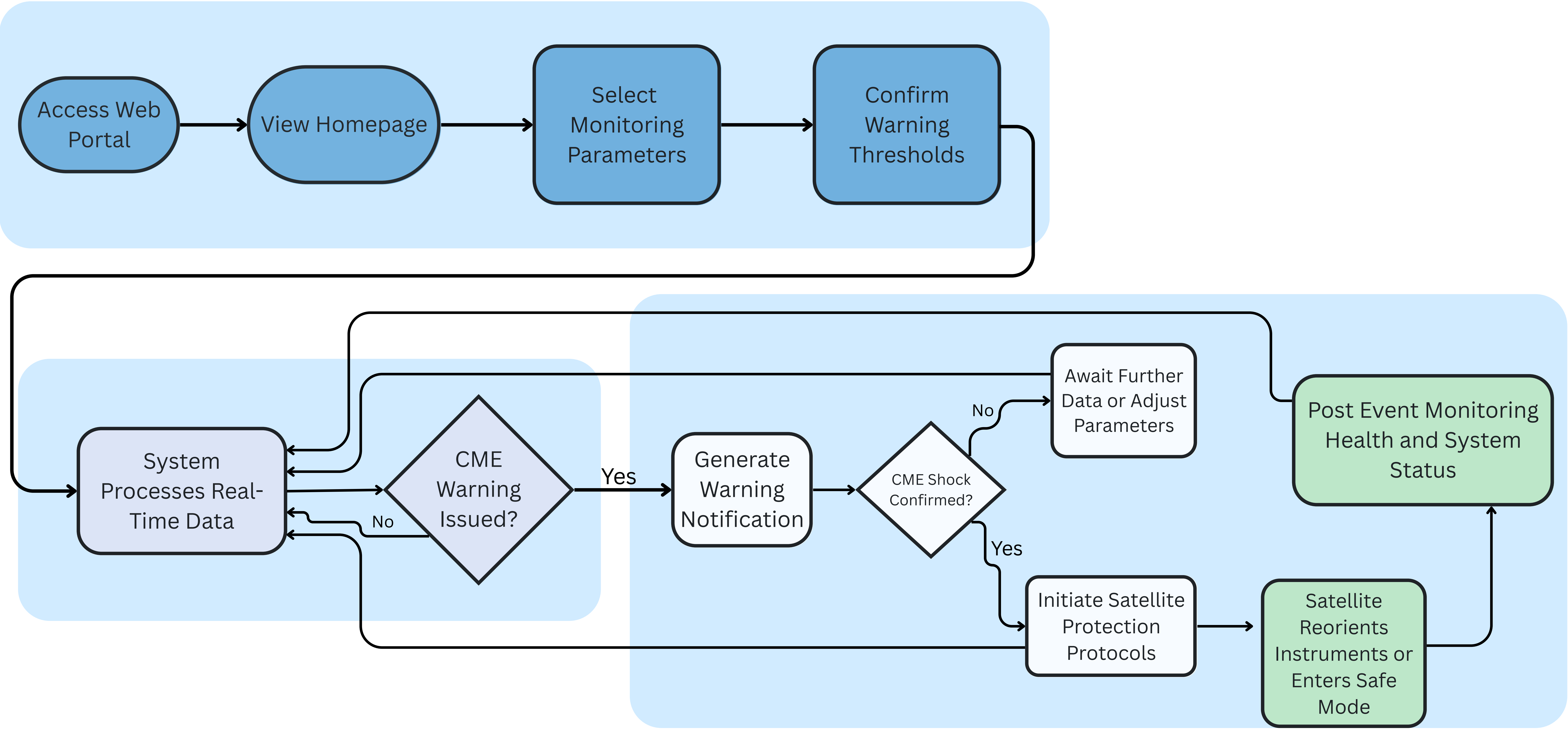
Physics Consistency Check	ML Architecture
• Plasma Beta (β) Analysis • MHD Flow Regime Classification (Mach Numbers) • Rankine–Hugoniot Filtering to Validate True Shocks • Mahalanobis Distance Anomaly Detection • Particle Flux Entropy Analysis • Entropy Gradient Shock Trigger	• Hybrid CNN–LSTM–Attention Architecture • Comprehensive Diagnostic Plots • Multi-Dimensional Anomaly Detection • Monte Carlo Uncertainty Estimation



The entropy gradient shows a sharp spike at the arrival of the CME, but once the spacecraft moves into the new plasma region—where the plasma's properties are no longer changing abruptly—it returns to a lower value

DATA USED: SWIS + MAG

Process flow diagram or Use-case diagram :-



Prototype Validation of the Features (Instead of Wireframe Optional)

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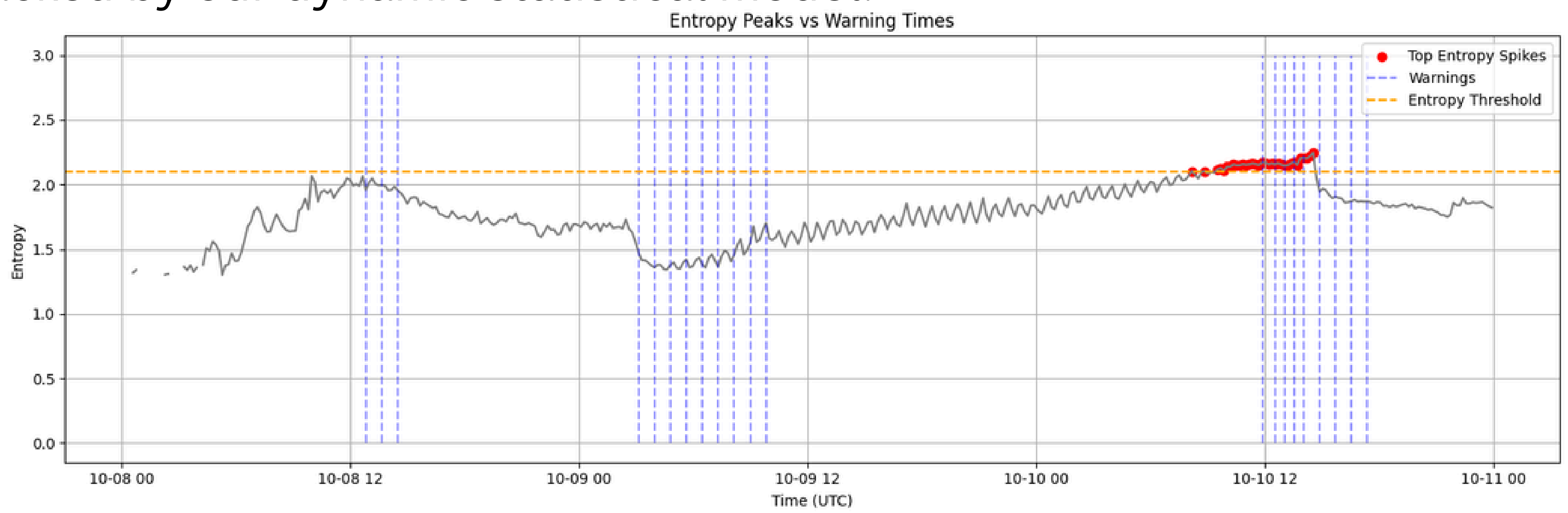
FEATURE 1

WHAT DID WE DO? (Applied on Real Aditya L1 data from ISSDC)

We conducted a detailed 72-hour statistical analysis on plasma and particle flux data from October 8–10, 2024, covering a period with known geomagnetic disturbances and potential CME shock activity.

WHAT WE FOUND?

Over the 3-day test window, we detected 21 distinct warning events, each backed by our dynamic statistical model.



TIME	FLUX ANOMALY	CONFIDENCE SCORE	ASSYMETRY DISTR.	CONCLUSION
2024-10-09 05:38	19.7×	1.00	No	Very strong early shock signal.
2024-10-10 11:51	1.2×	0.52	Yes	Likely CME front hitting L1.
2024-10-10 14:02	2.3×	0.63	Yes	Confirmed shock arrival(chotic plasma)
2024-10-10 14:52	13.5×	1.00	Yes	Major flux spike & confirmed CME hit

***Known CME Data taken from RIchardson & Cane**

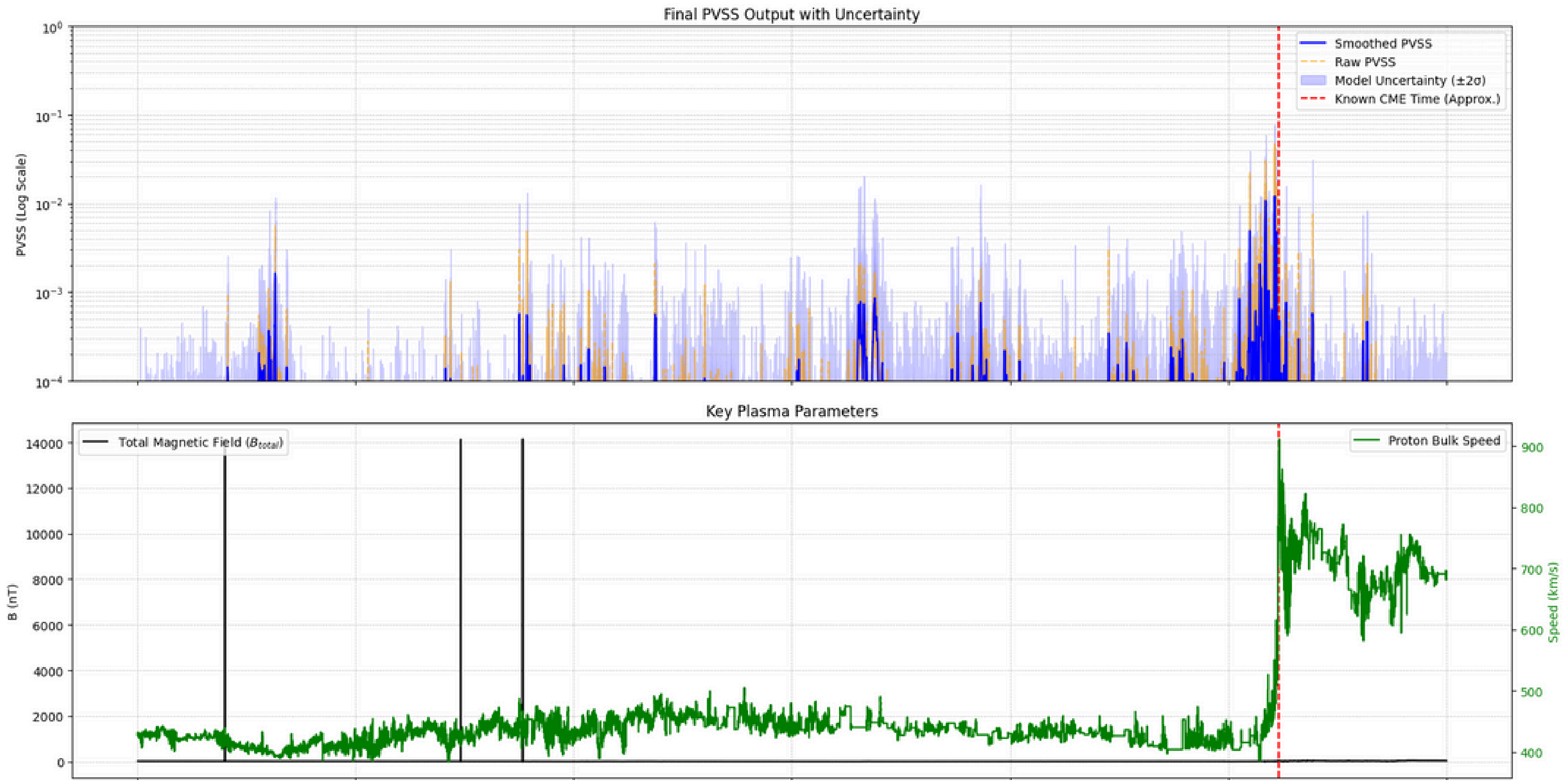
FEATURE 2

WHAT DID WE DO? (Applied on Real Aditya L1 data from ISSDC)

We deployed our custom deep learning model, which was trained on one month of solar wind data from August 2024, to autonomously monitor a 72-hour test period from October 8-10, 2024, known to contain a significant solar event.

WHAT WE FOUND?

- The model produced a sharp, high-confidence peak in its Physically Validated Shock Score (PVSS).
- The model's performance was highly sensitive to training duration. The optimal result was achieved with 4 training epochs.



***Google Colab links of our code**

Warning System Prototype

Realtime Shock Detection Prototype

Architecture diagram of the proposed solution

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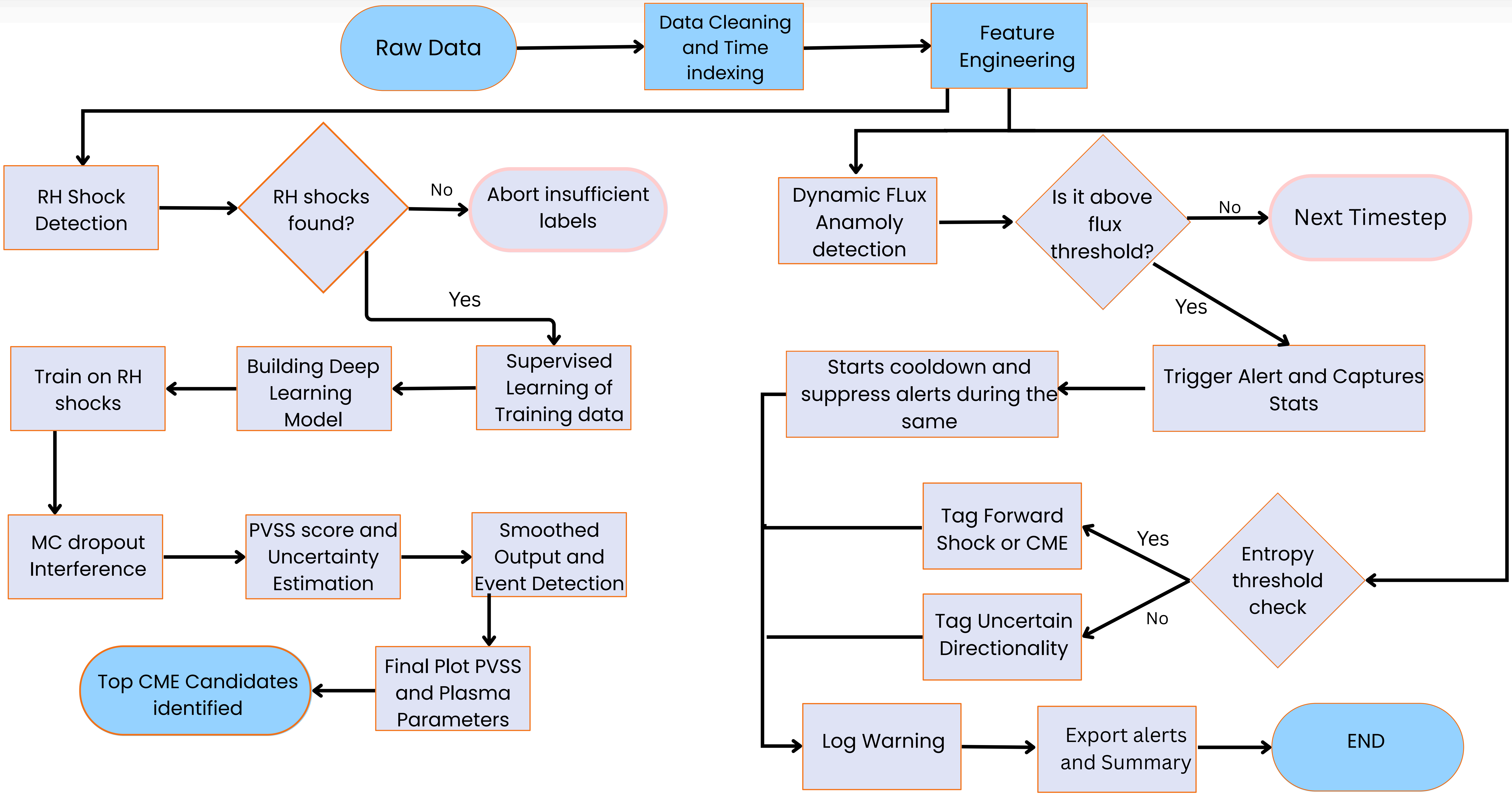

Technologies to be used in the solution:

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1. Programming Languages and Environment

Python, Google Colab, Pandas, NumPy, Matplotlib,Tensorflow,Keras:

- Python stack was chosen for its robust libraries, rapid prototyping capabilities, and powerful data manipulation tools.

2. Model Architecture Selection

- **FINAL MODEL**

1. Deep learning,CNN-LSTM-Attention architecture, which is specifically designed to learn from sequences of data.
2. In this model:**CNN** finds key local patterns, like shock spikes., **LSTM** understands the sequence—the story of how these patterns unfold over time, and the **Attention** layer focuses on the most critical moments of the event.

- **FAILED ATTEMPTS!!!!**

1.Simple linear model-couldn't handle the complexity

2.Logistic Regression-analyzed each moment in time independently and ultimately failed to capture the essential temporal dynamics.

3.XGBoost-overfit to noise in the data instead of learning the underlying physical sequence.

3. Advanced Anomaly Detection & Uncertainty Quantification

- **FINAL MODEL**

1.Dynamic Thresholding-using Rolling IQR.

2.Mahalanobis Distance-captures anomalies in full plasma vector space, not just scalar thresholds.

3.Monte Carlo Dropout-model outputs a confidence score for every alert — more interpretable & physically meaningful.

- **FAILED ATTEMPTS!!!!**

1.Fixed Thresholds- Didn't generalize across different solar wind conditions.

2.Single-Variable Checks -ignored correlation between key parameters (e.g., density, velocity, temperature).

Hybrid Physics + ML Approach (Instead of Optional Implementation Costs) Powered by H2S

- **Physics-Informed Feature Engineering**

1.Plasma Beta (β):

$$\beta = \frac{p_{thermal}}{p_{magnetic}} = \frac{nk_BT}{B^2/(2\mu_0)}$$

$\beta \gg 1$, the plasma is "thermally dominated."
$\beta \ll 1$, the plasma is "magnetically dominated.

- **CONCEPT-**CME is a fundamentally magnetic structure as its shock front compresses the interplanetary magnetic field, causing a sharp drop in Plasma Beta.

2.Alfven Speed and Mach Numbers:

$$v_A = \frac{B}{\sqrt{\mu_0 \rho}} \qquad M_A = \frac{V_{\text{bulk}}}{v_{\text{Alfvén}}} \quad , \quad M_s = \frac{V_{\text{bulk}}}{c_{\text{sound}}}$$

where,
v_A: Alfven Speed
M_A: Super-Alfvenic Mach no.
M_s: Supersonic Mach no.

- **CONCEPT-**A CME can only form a shockwave if it is traveling faster than the local signal speeds of the medium it's moving through.
- For a shock to exist a flow must be:
  (1)Super-Alfvénic (Ma>1) (2) Supersonic (Ms>1)

3. Cross Entropy Analysis

$$H(p,q) = -\sum_{i=1}^{n} p_i \log(q_i)$$

p_i: Normalized particle flux in **inner bins**
q_i: Normalized particle flux in **outer bins**

- **CONCEPT-**Particle distribution becomes anisotropic near a shock
- This creates a statistical difference between inner & outer detector bins.
- CME driven shock identified by strong assymmetry.

4. Rankine-Hugoniot (RH) Conditions:

$$\rho_1 v_1 = \rho_2 v_2 \text{ (Conservation of Mass)}$$

$$\rho_1 v_1^2 + p_1 + \frac{B_1^2}{2\mu_0} = \rho_2 v_2^2 + p_2 + \frac{B_2^2}{2\mu_0} \text{ (Conservation of Momentum)}$$

- **CONCEPT-** Density, temperature, and magnetic field must increase across a shock.
- **RH-QUALIFIED SHOCKS -** $\frac{\rho_{\text{down}}}{\rho_{\text{up}}} > 1.5$

5.Mahalanobis Distance:

$$D^2 = (\mathbf{x}-\boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x}-\boldsymbol{\mu})$$

$\mathbf{x}$: Current observation vector (e.g., plasma parameters)
$\boldsymbol{\mu}$: Mean of the background (quiet) window
Σ : Covariance matrix of the background data
Σ^{-1} : Inverse covariance matrix (accounts for correlations)
$(\mathbf{x}-\boldsymbol{\mu})^T$: Transpose of the deviation vector

- **CONCEPT-** Analysing the 4D plasma state vector x=[V,ρ,T,B].
- It measures the distance of a point from the center of a distribution, corrected for the correlation and scale of the variables much better than hardcoding thresholds.
- A high score means a point is a significant outlier in the *entire plasma state*, not just in one variable. This is how our code flags a shock_candidate.

***Written on Overleaf Latex Editor**

Planned Improvements and Enhancements

Improvement	Problem In Current Model	Idea
Physics-Calibrated Labeling System	• Labels currently based on hardcoded density thresholds (e.g., $\rho > 1.5$) • Ignores temp & magnetic jumps	• Use dynamic thresholds based on Mahalanobis zones & gradient spikes • Incorporate full shock physics (ρ, T, B)
Smart Shock Response Logic	• Persistence checks are fixed • Cannot adapt to spike severity	• Make persistence dynamic based on flux jump magnitude • Faster alerts for large spikes, slower for weak ones
Directional Anisotropy Integration	• Directional flux data underused • Cross-entropy not fully used	• Find a way to feed directional entropy directly into alert logic • Combine temporal + spatial energy patterns
Geo-Effectiveness Risk Index	• Alerts stop at "shock detected" • No link to real-world effects	• Estimate post-shock Bz evolution • Output a Geoeffectiveness score based on Bz duration & depth
Dynamic Persistence	The persistence check currently waits for a fixed number of steps before issuing an alert.	• Instant alert for strong spikes (e.g 100× flux -- 1-step trigger) • Longer wait for weaker spikes (e.g. 5× flux -- 4–5 steps) • Adapts in real-time to event strength -- balances speed vs. false positives

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THANK YOU