JSCER
ISSN: 2708-1079

Journal of Science, Computing and Engineering Research (JSCER)

Volume-9, Issue-3, March 2026.

IDENTIFYING HALO CME EVENTS BASED ON PARTICLE DATA FROM THE SWIS-ASPEX PAYLOAD ONBOARD ADITYA-L1

[1]Deepak Sharma,[2]Dhruv Saini,[3]Lily Singhal,[4]Ankit Yadav,[5]Mayank

[1] Professor, Department of CSE, Modern Institute of Technology and Research Centre, Rajasthan, India.

[2,3,4,5]UG Student, Department of AI&ML, Modern Institute of Technology and Research Centre, Rajasthan, India

Article Information

Received : 27 March 2026

Revised : 28 March 2026

Accepted : 29 March 2026

Published : 31 March 2026

Corresponding Author:

Dhruv Saini

Abstract— India's Aditya-L1 mission features the SWIS instrument that allows a continuous recording of the solar wind ion flux, energy, and directional properties. For this purpose, it uses two Top- Hat Analysers covering 0.1–20 keV with full 360° angular coverage. The magnetic mass analyser in THA-1 separates H^+ from He^{2+}, thus allowing the accurate monitoring of helium abundance changes that frequently occur during the passing of halo CMEs and the structures connected to them. Such measurements provide a timeline for the arrival of the CME through the detection of early signatures like ion composition changes, speed, and High-Speed particle levels. By observing the time-dependent changes of the solar wind parameters measured by SWIS, the research intends to enhance the short-term forecasting of halo CME arrival at L1 and deepen the understanding of their impact. The multi-directional and adjustable configuration of the instrument enables it to keep a continuous record of the disturbances in the Heliosphere layer and be able to anticipate space weather.

Keywords— Halo Coronal Mass Ejection, CME Arrival Prediction, Solar Wind Ion Spectrometer (SWIS), Solar Wind Composition, Solar Wind Velocity, Lagrange Point L1.

Citation *: Deepak Sharma, Dhruv Saini, Lily Singhal, Ankit Yadav, Mayank* *" IDENTIFYING HALO CME EVENTS BASED ON PARTICLE DATA FROM THE SWIS-ASPEX PAYLOAD ONBOARD ADITYA-L1 "****,*** *Journal of Science, Computing and Engineering Research, 9(03), March 2026****.***

I. INTRODUCTION

The solar wind constitutes ionized plasma of the Sun's billion-degree corona is carried away from the Sun into the interplanetary medium by the solar wind, the particle flux is driven by the million-degree corona. This flow conserves the overall conditions of the heliosphere, in the slow and fast streams of about 300–500 km s^{-1} and 500–750 km s^{-1}, respectively, during quiet times, and each comes from a different solar region. While the solar wind establishes the average state of the heliosphere, explosive releases of energy in the form of transient events, such as CMEs, produce sudden and Among these, halo CMEs, the ones whose expansion seems to wrap the solar disk, are relatively important since Earth- directed halo CMEs can compress the magnetosphere and cause moderate to intense geomagnetic storms. These, in turn, influence satellite operations, navigation networks, radio communication, and power-grid stability, making an early and accurate prediction of halo CME arrivals a priority in space-weather forecasting. Fractional plasma solar wind observations are necessary to the result of CME-induced shocks. Compositionally, the solar wind is primarily made up of protons (H^+), alpha particles (He^{2+}), and trace heavy ions.. Parametric changes such as sudden changes in velocity, heightened density, temperature decreasing, or He^{2+}/H^+ abundance ratio altering, are all the first indicators of CME movement. Continuous measurements from spacecraft located at the Sun–Earth L1 point, such as ACE, Wind, DSCOVR, and SOHO, on the one hand, and close to the Sun from missions like Parker Solar Probe and Solar Orbiter on the other, have helped considerably in understanding the evolution of CMEs. Nevertheless, the problem of uncertainties in their arrival time predictions is still so big that it is often more than a couple of hours away because a real prediction depends on a very complicated interaction of a CME with the background solar wind, for which high- cadence, species-resolved ion measurements are only seldomly available.

Aditya-L1 is India's ambitious project that is adding an entirely new dimension to the capabilities of the present solar physics missions. The mission was launched in September 2023 and has been operating in a halo orbit around the L1 point since January 2024.

The mission is equipped with a variety of instruments for imaging as well as in situ observations of the Sun.

Among the experiments carried out on the Indian Aditya-L1 mission, the solar wind particle experiment (ASPEX) is the most prominent and important, and it affords the continuous observation of solar-wind ions through two distinct subsystems: the solar wind ion spectrometer (SWIS) and the supra-thermal and energetic particle spectrometer (STEPS). SWIS with two Top-Hat electrostatic analysers covering a full 360° angle can carry out measurements of ion fluxes, directional anisotropies, and electron-resolved energy distributions in the energy range of 0.1–20 keV. By its inherent ability, SWIS can separate proton and alpha particles and as a result, detailed tracking of helium abundance can be achieved—this can be used as a key tool for the identifications of the CME and solar-wind source regions. The fact that SWIS is highly precise and can monitor several directions simultaneously at short intervals means that it becomes possible to notice those really faint, early-stage plasma signatures from which the subsequent arrival of the halo CME can be inferred .

Since the performance of reliable solar-wind diagnostics is a prerequisite for the prediction of geomagnetic disturbances, the information produced by SWIS may have a considerable impact on the development of models predicting arrival times and therefore on the improvement of those models. It is by examining solar wind variable data that SWIS is storing that we can discover the phenomenon of the solar wind precursors to the CME propagation and, therefore, better estimate the time window of CME arrival at L1. This research is targeted at discovering and proving that potential.

I. PROBLEM STATEMENT

Coronal Mass Ejections (CMEs) are among the most powerful and disruptive forms of solar activity. These events involve the sudden release of huge quantities of plasma and magnetic fields from the Sun's corona into interplanetary space. When such an eruption is directed toward Earth, it appears as a "halo" around the Sun in coronagraph images, and is therefore known as a Halo CME. Halo CMEs are especially important because they travel along the Sun–Earth line and can directly interact with Earth's magnetic field. As the modern world increasingly depends on satellites, navigation systems, radio communication, aviation networks, and electrical power grids, the timely detection of Halo CMEs has become a critical requirement.

India's Aditya-L1 mission, positioned at the Lagrange Point L1, is designed to study the Sun continuously and provide early insights into solar disturbances. The SWIS–ASPEX payload onboard Aditya-L1 measures important solar wind ion parameters, including flux, velocity, density, and temperature. These measurements are essential for identifying the physical signatures of CMEs as they propagate through space. However, Aditya-L1 generates vast amounts of multi-parameter data every day. This data is highly dynamic, often noisy, and influenced by several overlapping solar phenomena. As a result, manually examining the data or using simple threshold-based rules is inefficient, inconsistent, and often inaccurate.

Because Halo CMEs can severely affect satellites, disrupt GPS signals, interfere with communication systems, and even impact power infrastructure on the ground, there is a strong need for a more reliable and automated detection mechanism. Solar wind disturbances associated with CME events often involve complex patterns such as sudden velocity jumps, density enhancements, temperature fluctuations, and shock signatures. Detecting these patterns requires systematic processing of large time-series datasets, advanced feature extraction, and intelligent decision-making rather than manual inspection.

The real challenge lies in the complexity and variability of the data obtained from the SWIS–ASPEX payload. Solar wind behaves in a non-linear manner, and different parameters may react differently to CME-driven shocks. Noise, data gaps, and sudden fluctuations add to the difficulty. Threshold-based methods may miss weaker CME signals or produce false detections during normal solar wind variations. Therefore, a more robust, automated method is required—one that can process the data, identify anomalies, and determine the presence of Halo CME events with higher accuracy.

This project aims to address this challenge by developing an automated Halo CME detection system using Aditya-L1 particle flux and solar wind data. The system is designed to read input data, clean and validate it, extract meaningful features, detect CME-related disturbances, classify events, and generate results that can be visualized or used for further analysis. By automating the detection process, the project seeks to provide early indications of CME events that can support space weather forecasting agencies in issuing timely alerts. The importance of this work extends beyond scientific interest. Halo CMEs can affect critical areas such as:

- Satellite communication and TV broadcasting
- GPS navigation systems used in aviation, ships, and road transport
- Internet connectivity through satellite links
- Spacecraft operations and astronaut safety
- High-frequency radio communication used in defense and emergency systems
- Power grid stability during strong geomagnetic storms

Given these risks, developing a reliable Halo CME detection tool contributes to both technological safety and national preparedness.
The automated system developed in this project uses the Aditya-L1 dataset along with external CME catalogs, such as the CACTUS CME list, to validate and refine event identification. The model detects solar wind anomalies by analyzing variations in velocity, density, temperature, and particle flux, and generates a combined score to classify the presence of a possible Halo CME. This automated approach ensures faster processing, reduced human error, and more consistent detection compared to manual analysis.

The scope of this project includes data collection, preprocessing, anomaly detection, scoring, visualization, and generating outputs that can support researchers and space weather forecasters. While the project does not extend to CME arrival forecasting or impact prediction, it lays the groundwork for such future studies. Developing such a detection pipeline is essential for improving India's capability in solar monitoring and enhancingreadiness against space weather threats.
In summary, the core problem addressed by this project is the need for a robust and automated Halo CME detection model capable of handling large volumes of Aditya-L1 particle data and accurately identifying CME signatures. By solving this problem, the project contributes to advancing solar research, improving space weather monitoring, and protecting technological infrastructure that is vital for communication, navigation, and national security.

II. PROPOSED MODEL

The proposed model presents a structured pipeline for real-time detection and forecasting of Coronal Mass Ejections (CMEs) using multi-source space weather data. The system integrates data ingestion, preprocessing, feature engineering, and machine learning-based detection within a scalable architecture.

It further ensures continuous data flow, real-time analysis, and accurate prediction of space weather events through an efficient and modular design.

System Workflow

1. **Data Sources:** The system collects data from multiple sources including SWIS Level-2 datasets, NOAA space weather data, OMNIWeb solar wind data, and CACTUS CME catalog for labeled events.
2. **Data Ingestion:** Automated data fetching mechanisms are used to retrieve real-time and historical data. Time alignment and window selection techniques ensure consistency across different data streams.
3. **Preprocessing:** The collected data undergoes preprocessing steps such as missing value handling, noise filtering, and background solar wind modeling. CME event windows are tagged using reference timestamps.
4. **Feature Engineering:** Relevant features such as moving averages, temporal gradients, variance metrics, He^{2+}/H^{+} ratio, and composite disturbance indices are extracted to represent underlying patterns in the data.
5. **Detection and Modeling:** Satistical and machine learning-based techniques, including threshold modeling, z-score deviation detection, and change-point detection, are applied to identify CME events.
6. **Model Training (Offline):** The system is trained using labeled CME and non-CME intervals. Cross-validation and hyperparameter tuning are performed to improve model accuracy and generalization.
7. **Model Serving (Online):** The trained model is deployed for real-time inference, generating detection flags, probability scores, and CME arrival window estimations .
8. **Storage:** Processed datasets, detection results, event metadata, and system logs are stored for future analysis and evaluation.
9. **Visualization and Dashboard:** The results are presented through an interactive dashboard, including time-series plots, detection indicators, performance metrics, and early warning alerts.

Final Outcome

The proposed model enables accurate real-time CME detection, efficient data processing, and intuitive visualization, supporting continuous monitoring and decision-making in space weather analysis.

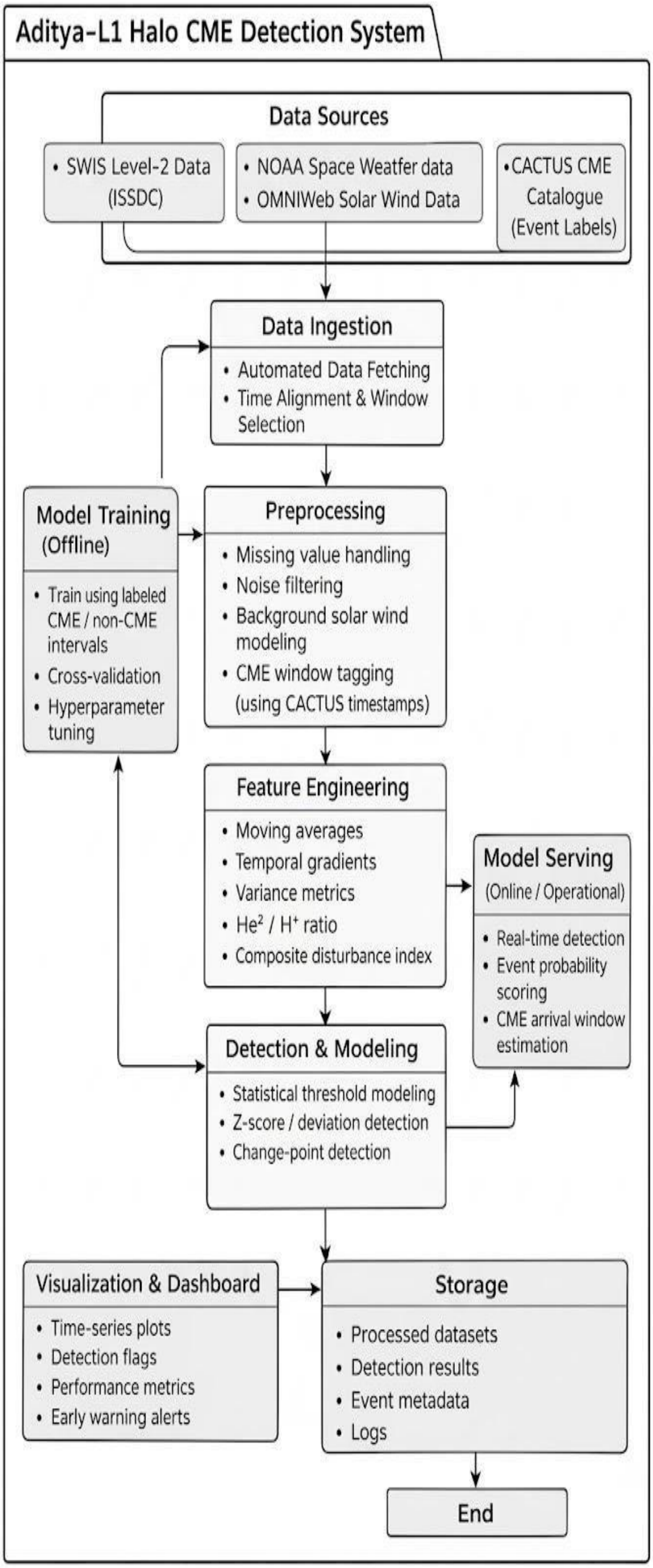

Fig. 1. Component Diagram

III. TECH STACK

A. Frontend Development (React.js)

The frontend is developed using React, a modern JavaScript library for building interactive user interfaces..

- It follows a component-based architecture, improving modularity and code reusability.
- React utilizes a virtual DOM, enabling efficient and fast rendering of dynamic content.
- The framework provides flexibility for designing scalable and interactive dashboards.
- The developed interface presents event summaries, time-series visualizations, detection scores, and other analytical insights.
- Overall, React ensures a responsive, efficient, and user-friendly frontend system.

B. Backend Development (FastAPI)

The backend is developed using FastAPI, providing a fast, scalable, and efficient framework for building RESTful APIs..

- FastAPI handles client requests and supports asynchronous processing for efficient real-time data handling..
- The backend manages functionalities such as serving detected events, triggering data processing jobs, providing visual plots, and handling metadata.
- Dedicated worker scripts perform tasks such as data loading, preprocessing, feature extraction, detection, and scoring.
- The system separates API handling and computational processing to ensure that the backend remains lightweight and responsive..

C. Data Visualization Tools (Machine Learning)

The system utilizes Python-based data visualization libraries to analyze and present machine learning results effectively.

- Matplotlib is used for generating basic plots such as line graphs and time-series visualizations.
- Seaborn is used for advanced statistical visualizations and pattern analysis.
- Plotly is used to create interactive and dynamic visualizations for better data exploration.
- These tools are used to visualize trends, feature distributions, model outputs, and forecasting results.
- The generated visualizations help in understanding patterns in space weather data and evaluating model performance.

D. Deep Learning Algorithms (LSTM, RNN)

The system utilizes deep learning algorithms to model complex temporal patterns and improve the accuracy of space weather predictions.

- Long Short-Term Memory (LSTM) networks are used for time-series forecasting of parameters such as Dst index, Kp index, sunspot numbers, and ap index.
- Recurrent Neural Networks (RNN) are applied to capture sequential dependencies in space weather data.
- Deep learning models are trained on historical datasets to learn long-term trends and variations.
- These models enable the system to handle non-linear patterns and improve prediction performance.
- The outputs of deep learning models are used for CME detection, scoring, and future forecasting.

E. System Modelling & Design (StarUML + Figma)

Before development, detailed system modelling is performed to ensure clarity and minimize architectural issues.

- System diagrams such as Use Case, Class, Activity, and Sequence diagrams are created using StarUML to represent workflows including data ingestion, processing pipelines, API interactions, and dashboard communication..
- UI/UX mockups and user flow diagrams are designed using Figma to prototype the space weather dashboard and optimize user interaction with real-time data and visualizations.
- These design approaches help in structuring the system efficiently, identifying data flow between components, and reducing implementation complexity.

F. API Testing and Validation (Postman)

All backend endpoints are thoroughly tested using Postman to ensure reliable communication between the frontend dashboard and backend services.

- Each API is tested for data validation, performance, security, and proper error handling.
- Test cases simulate real-time scenarios such as fetching CME events, retrieving forecasts, and accessing space weather data.
- APIs related to composite index generation, model accuracy, and real-time data feeds are validated for correctness and consistency.
- These testing practices ensure accurate data delivery, system stability, and robust performance under continuous data updates.

G. Modular and Scalable Architecture

The system follows a modular architecture that supports future expansion:

- New data sources such as additional satellite feeds or space weather APIs can be integrated without affecting existing functionality.
- Advanced machine learning and deep learning models can be incorporated to improve prediction accuracy and detection capabilities.
- Additional analytical features, dashboards, or visualization modules can be added seamlessly.
- The modular design ensures easy maintenance, flexibility, and efficient system upgrades.

IV. RESULT SCREENSHOT

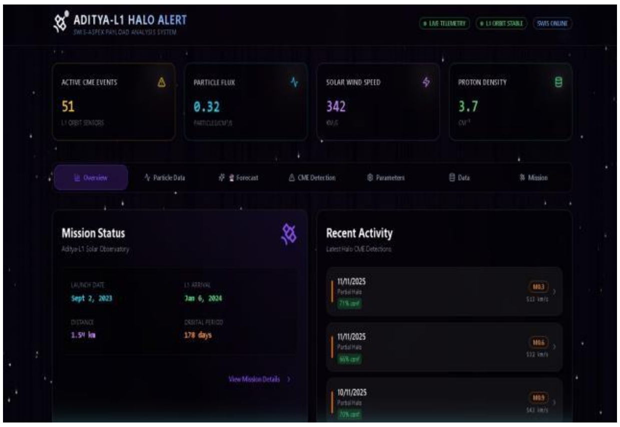

Fig. 2.

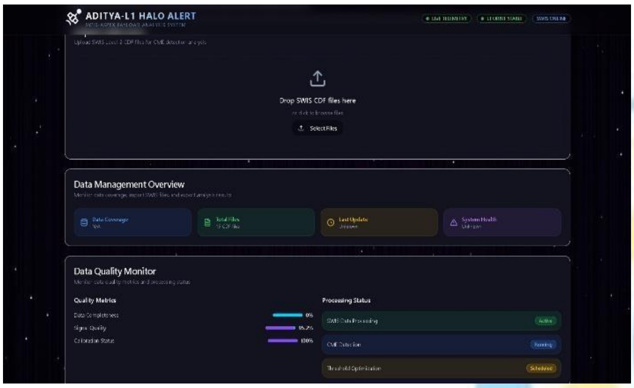

Fig. 3.

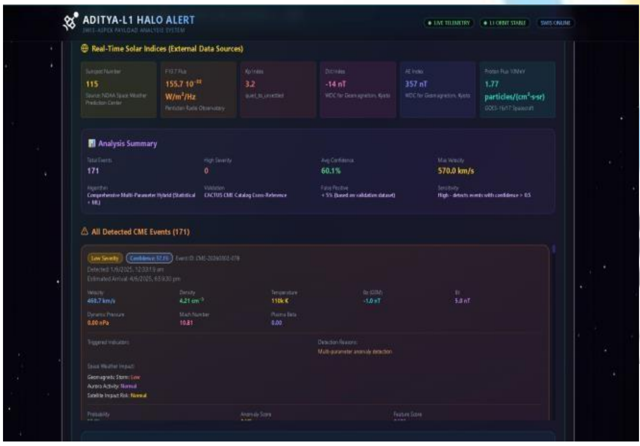

Fig. 4.

V. CONCLUSION

This research presents an advanced system for real-time detection and forecasting of Coronal Mass Ejections (CMEs) using multi-source space weather data. The proposed model integrates data ingestion, preprocessing, feature engineering, and machine learning-based detection within a scalable and modular architecture. The system efficiently processes large volumes of heterogeneous space weather data and generates accurate detection results along with reliable predictive insights.

The implementation demonstrates the effectiveness of combining statistical techniques with machine learning and deep learning approaches for identifying CME events and analyzing temporal patterns. The use of feature engineering and time-series modeling enhances the system's ability to capture complex variations in solar activity. Additionally, the separation of data processing and API layers ensures high performance, responsiveness, and maintainability.

The developed interactive dashboard further strengthens the system by providing intuitive visualizations, real-time monitoring, detection scores, and forecasted parameters. This enables users to better understand space weather trends and supports informed decision-making. The modular architecture of the system allows easy integration of additional data sources, improved models, and extended analytical capabilities.

Overall, the system provides a reliable, scalable, and efficient solution for continuous space weather monitoring and CME detection. In future work, the system can be enhanced by incorporating more advanced deep learning models, improving prediction accuracy, and expanding real-time data integration to support early warning systems and broader scientific research applications.

REFERENCES

1. M. Bauer, "Solar Transient Recognition Using Deep Learning (STRUDL) for Heliospheric Imager Data," 2025.

2. S. K. Goyal et al., "Aditya Solarwind Particle Experiment (ASPEX) onboard the Aditya-L1 mission," *Planetary and Space Science*, 2018.

3. T. Rüdisser, "ARCANE – Early Detection of Interplanetary Coronal Mass Ejections," 2025.

4. N. Gopalswamy *et al.*, "Radio-Rich Solar Eruptive Events," *The Astrophysical Journal*, 2010.

5. K. D. Leka and G. Barnes, "Solar Flare Forecasting: Present Methods and Challenges," Predictive Science Inc., 2018.

6. A. Vourlidas *et al.*, "The Coronal Mass Ejection Visibility Function of Modern Coronagraphs," *Solar Physics*, 2013.

7. P. Riley, "On the probability of occurrence of extreme space weather events," *Space Weather*, vol. 10, no. 2, 2012.

8. R. Patel et al., "Onboard Automated CME Detection Algorithm for Visible Emission Line Coronagraph on ADITYA-L1," *Solar Physics*, 2018.

9. P. Kumar et al., "Aditya Solar Wind Particle Experiment (ASPEX) onboard Aditya-L1: The Solar Wind Ion Spectrometer (SWIS)," *Solar Physics*, 2024.