Machine Learning Algorithms for Autonomous Space Mission Operations

T. Torda [1] T. Alberti [1] N. Chrysaphi [2] R. De Marco [1] E. Dineva [3] J. Eklund [4] P. Gonidakis [3] M. Laurenza [1] M.F. Marcucci [1] S. Markidis [4] G. Miloshevich [3] S. Poedts [3] B. Sanò [5]

[1]INAF-Institute of Space Astrophysics and Planetology (IAPS), via del Fosso del Cavaliere 100, 00133, Roma, Italy, [2]CNES, 2 place Maurice Quentin, 75039 Paris, France, [3]KU Leuven, Oude Markt 13, 3000 Leuven, Belgium, [4]KTH, Brinellvägen 8, 114 28 Stockholm, Sweden, [5]Università di Trento, Via Calepina, 14, 38122 Trento TN

Abstract

The Automatics in SpAce exPloration (ASAP) project has as a goal the design and development of Machine Learning (ML) algorithms for the automation of operations to be implemented on the on-board processors of space missions. In the framework of ASAP, a set of ML algorithms for on-board science operations of space missions have been developed/optimized on consumer-grade computing systems to be further selected for porting of existent ML models directly on an FPGA prototype. In more detail, algorithms pertaining to four main use cases have been considered: the autonomous triggering of special measurement modes and the selective downlink of plasma environment parameters; the advanced on-board data analysis of three-dimensional particle distribution functions; the on-board analysis of solar images; the on-board prediction capability of SEP related hazards. Here, we give a description of four algorithms, for further algorithms go to see also "Gonidakis, P., Carella, F., Miloshevich, G., and Poedts, S.: Efficient Segmentation and Clustering of Solar Coronal Structures: A Comparison of U-Net and Classical Computer Vision Techniques Using SDO Data, EGU General Assembly 2025, Vienna, Austria, 27 Apr–2 May 2025, EGU25-9849". ASAP has received funding from the HORIZON Research and Innovation Action of the EU (GA no.101082633)

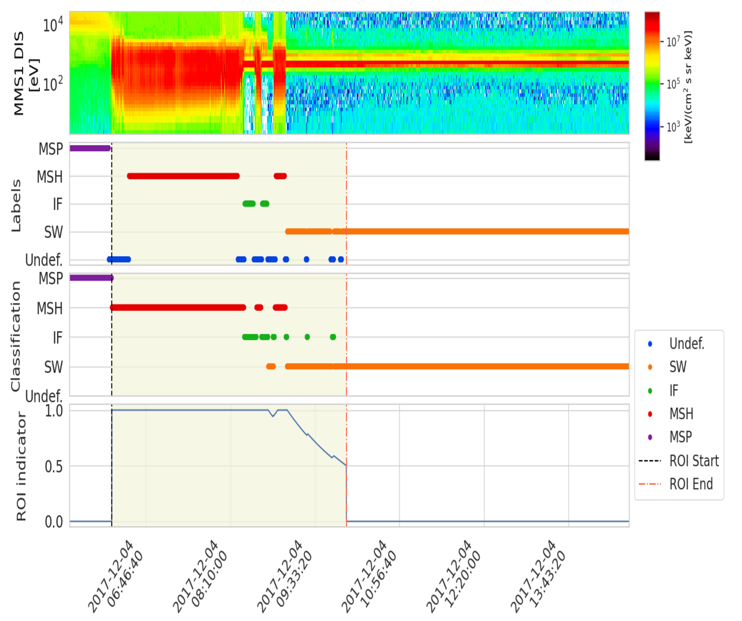
Burst triggering and selective downlink algorithms

Modern spacecraft generate vast amounts of data, often exceeding downlink capacity, especially in multi-spacecraft missions. To address this, onboard AI processing can be used to optimize data collection and transmission by identifying regions of scientific interest in space and prioritizing high-value data. Two primary use cases for AI-driven data prioritization are:

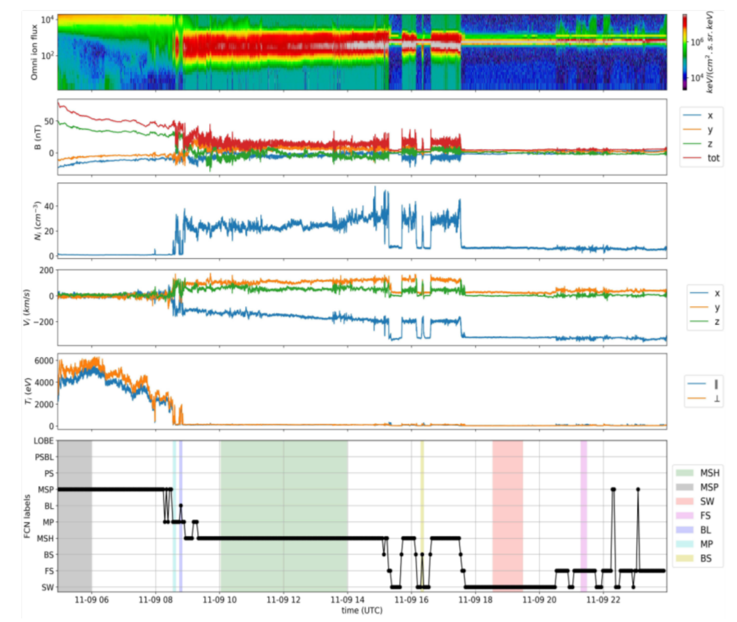
- Selective Downlink of Scientific Data:
  A Convolutional Neural Network (CNN) classifies and prioritizes data for transmission, reducing storage demands and improving efficiency, particularly for deep-space missions.
- Region of Interest (ROI) Identification for High-Rate Data Collection:
  AI can detect high-value data in key regions such as the magnetopause and bow shock, conserving resources and capturing rare events.

The models

- **CNN model:** The CNN model used for classification follows the topology of Olshevsky et al. (2021) [1], categorizing plasma regions into solar wind (SW), ion foreshock (IF), magnetosheath (MSH), or magnetosphere (MSP). This model has been optimized significantly by reducing its size while maintaining prediction accuracy (Ekelund et. al. 2024 [2]): achieves a 95%–98.9% size reduction with minimal accuracy loss, enabling faster inference and lower power consumption, Figure 1a.
- **Short Time Fourier Transforms model:** A second approach leverages image analysis to detect transition regions and trigger burst mode acquisitions. This method applies Short Time Fourier Transforms (STFT) to time-series observations, forming multi-channel images for analysis. Previous work (Breuillard et al., 2020 [3]) demonstrated the effectiveness of this method when applied to MMS data, Figure 1b.



(a) Region of interest detection with baseline CNN applied to MMS data.

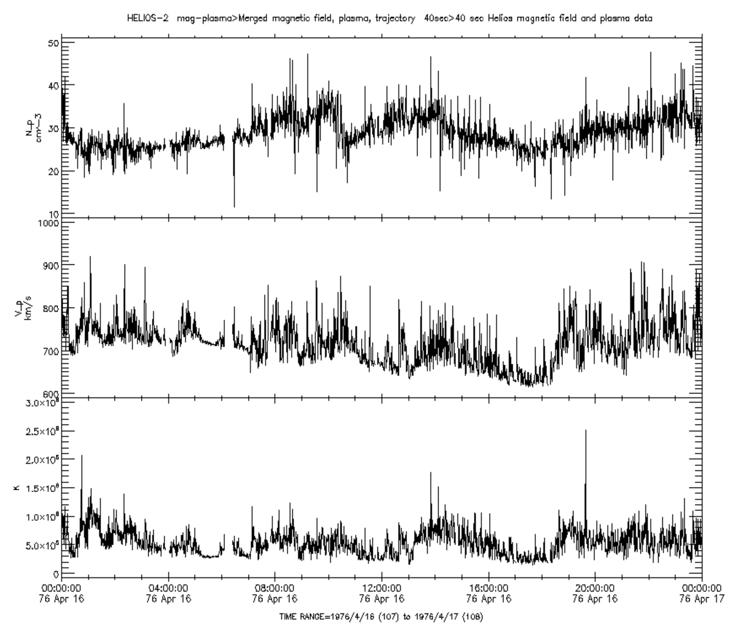


(b) MMS dayside classification. Breuillard et al, 2020 [3]. Work part of AIDA.

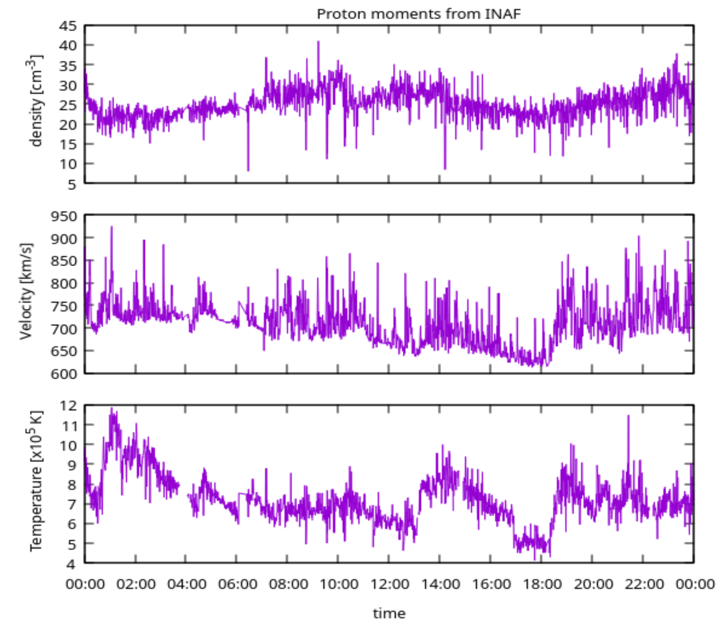
Figure 1. Results from the Neural Network models

On-board analysis of particle velocity distribution functions

Velocity Distribution Functions (VDFs) provide key macroscopic plasma properties such as density, velocity, and temperature. VDFs must be defined for each particle species. Ion detectors measure directional distributions and energy-per-charge (E/q) spectra, leading to ambiguities in species identification. In the solar wind, protons and alpha particles can be separated post-measurement using fitting procedures, though strong overlaps can hinder accuracy. We propose clustering VDFs using Gaussian Mixture Models (GMMs) to distinguish overlapping ion populations. Here, we present an application to the solar wind sampled by Helios 2 on 16 April 1976, when the spacecraft was at a distance of 0.29 au from the Sun. We separated the VDF into protons and alpha particles and computed density, velocity, and temperature. These can be compared to the time series available on the CDAWeb repository (https://cdaweb.gsfc.nasa.gov). As can be seen from the Figure 2, the proton moments are similar (differences can also be due to differences in moments computation).



(a) Proton moments of 16 April 1976 from Helios 2, time series from CDAWeb



(b) Proton moments of 16 April 1976 from Helios 2, our results

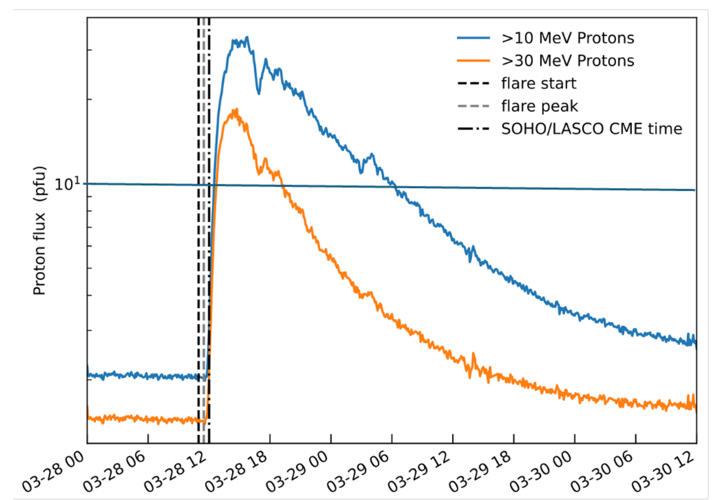
Figure 2. Proton moments of 16 April 1976 from Helios 2

SEP prediction algorithm: ESPERTA on board

ESPERTA (Empirical model for Solar Proton Events Real Time Alert) is a forecasting method designed to predict the occurrence of an SEP event 10 minutes after the peak of any flare of class greater or equal to M2 occurring on the Sun. To achieve this, ESPERTA is based on three variables:

- Helio-longitude of the flare;
- Time-integrated Soft X-Ray (SXR) flux;
- Time-integrated 1 MHz radio flux.

Previously optimized for forecasting SEPs with peak flux $\geq$ 10 pfu ($\geq$ S1 storms) [4], we now apply machine learning techniques to enhance early warnings also for high-intensity SEPs ($\geq$ 100 pfu, $\geq$ S2 storms) [5]. In order to use ESPERTA on board spacecraft at any location in the Heliosphere, we adapted and validated ESPERTA by using particle data from STEREO-A. We compiled a catalogue of SEP events observed by STEREO-A from 2009 to 2022, where >10 MeV proton flux exceeded 10 pfu (see Figure 3 fo results).



(a) Proton flux at >10 MeV and > 30 MeV obtained from the STEREO-A LET and HET STEREO-A data for the 28 March 2022 SEP event. The Cyan horizontal line indicates the 10 pfu threshold used to define a SEP event.

Metric	Value (%)
Probability of Detection (POD)	88
False Alarm Rate (FAR)	32

(b) Best scores for the optimal threshold of 0.36

Solar flare prediction using CNNs

We develop a system of independent CNN in order to to predict soft X-ray flux using full disk images of the sun obtained from the Solar Dynamics Observatory (SDO). Each CNN will process inputs from different SDO channels (see Figure 4).

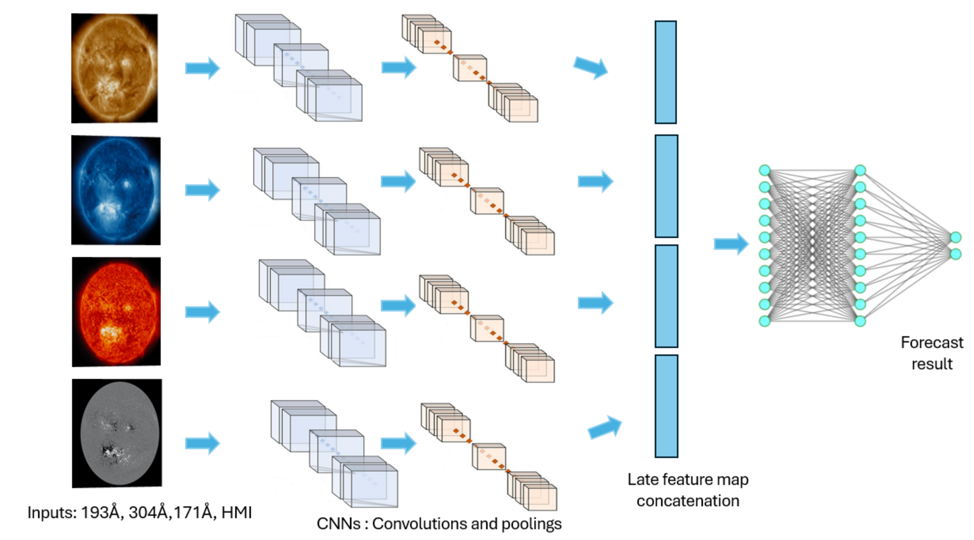


Figure 4. An example of a learning scheme using independently trained CNNs

We have explored a simple CNN architecture, while using a specialized loss function to improve the prediction of the extremes of the X-ray flux, a continuous quantity. It is a combination of Bernoulli random variable cross-entropy and mean square error:

$$\sum_{n=1}^{N}\left[-\mathbb{1}(Q=0)w_1 r\log(1-\hat{Q})+\mathbb{1}(Q\neq 0)w_2(I)\left(-r\log\hat{Q}+(I-\hat{I})^2\right)\right] \tag{1}$$

Here, indicator functions are specified for Q = 0 - no flare and Q = 1 - flare cases. "I" stands for intensity of the soft X-ray flux, and other parameters are weights chosen based on the distribution of the soft X-ray flux variable, which follows the Cauchy distribution [6]. Preliminary results on data from May 2012 have shown promising potential for our method (see Figure 5)

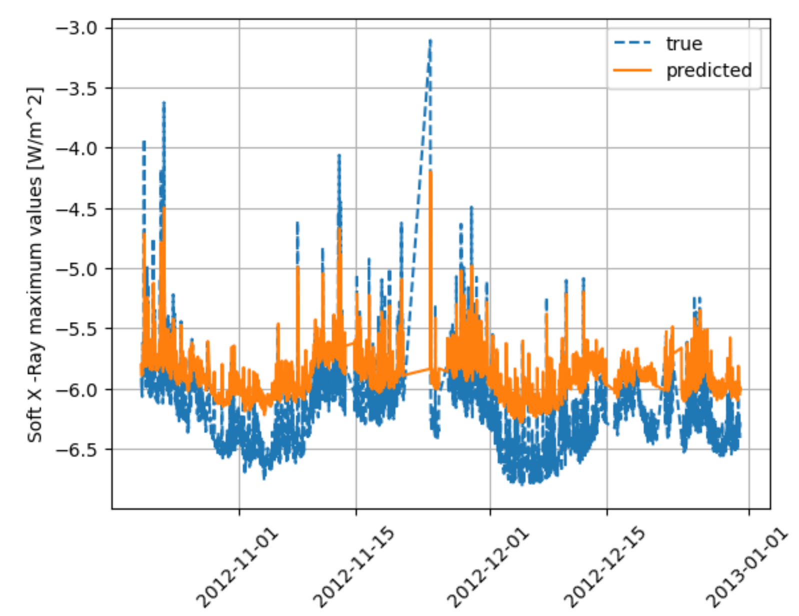


Figure 5. Performance of the detection tool, trained on preliminary 9 month long dataset and tested on November - December

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