Artificial Intelligence for the Analysis of Solar FLARES Data (AI-FLARES)

(PI: Michele Piana, MIDA, Dipartimento di Matematica, Università di Genova)

AI-FLARES Objectives

The 'Artificial Intelligence for the analysis of solar FLARES (AI-FLARES)' project had three scientific objectives and one technological goal. The scientific objectives were:

- To reconstruct the saturated EUV signal in the core region of images of flaring storms recorded by the Atmospheric Imaging Assembly (AIA) on-board the NASA Solar Dynamics Observatory (SDO).
- To provide an imaging-spectroscopy picture of the acceleration mechanisms at the base of solar high-energy emissions by applying regularization methods to photon visibilities recorded by both the NASA Reuven Ramaty High Energy Spectroscopic Imager (RHESSI) and the ESA Spectrometer/Telescope for Imaging X-rays (STIX) on-board Solar Orbiter.
- To design flare forecasting processes and to identify the most significant precursors of intense flares by applying machine learning and deep learning algorithms to the Helioseismic and Magnetic Imager (HMI) on-board SDO.

A further technological objective of AI-FLARES was to set up a computational corpus of data analysis methods that can be used as an up-to-date service for the interpretation of flare-related physics.

AI-FLARES team

AI-FLARES initial team was composed by:

- Michele Piana (MIDA, Dipartimento di Matematica, Università di Genova), the AI-FLARES Principal Investigator, who coordinated the whole project's effort and mainstreamed the dissemination of its results.
- Federico Benvenuto (MIDA, Dipartimento di Matematica, Università di Genova), who mainly focused his activity on the de-saturation of AIA EUV maps.
- Anna Maria Massone (MIDA, Dipartimento di Matematica, Università di Genova), who mainly worked at the formulation, implementation, and validation of computational methods for imaging spectroscopy from RHESSI and STIX visibilities.
- Cristina Campi (Dipartimento di Matematica, Università di Padova), who focused on the realization of machine learning algorithms for solar flares forecasting from HMI magnetograms.

By exploiting the project's financial support, AI-FLARES hired three post-doc researchers who contributed in a decisive way to the achievements of all project's goals. More specifically:

- Paolo Massa began working at AI-FLARES as an unfunded member, when he was finishing his PhD effort at the Università di Genova. Then he obtained a post-doc position that was supported by AI-FLARES. During this period, Paolo worked at the formulation and implementation of imaging and imaging spectroscopy approaches for the analysis of RHESSI and STIX visibilities and at the interpretation of AIA EUV maps
- Francesco Marchetti obtained a post-doc position at the Università di Padova, thanks to the AI-FLARES financial support. During this period, he worked at the design of

machine/deep learning networks for flare forecasting and at the implementation of the corresponding Python codes.
- Emma Perracchione was an AI-FLARES post-doc at MIDA, Dipartimento di Matematica, Università di Genova. Her position was mainly devoted to the formulation and implementation of numerical approximation schemes for image reconstruction in the RHESSI and STIX contexts.

All these three researchers kept on providing significant contributions to the scientific development of AI-FLARES even after the end of their respective contracts.

Other important contributions to the realization of AI-FLARES objectives came from young scientists who represented a crucial added value to the scientific success of the project. Among them, Sabrina Guastavino significantly contributed to the formulation of an effective de-saturation algorithm for saturated SDO/AIA maps, and inspired and realized several of the AI-based algorithms for flare forecasting developed within the project; Anna Volpara provided important contributions to the formulation and implementation of hard X-rays imaging spectroscopy algorithms, and was determinant to set up a formal mathematical model for the data formation process in STIX; Sara Garbarino collaborated with the AI-FLARES team to the formulation of an AI-inspired approach to parametric imaging for STIX. Finally, Rosario Messineo and Filomena Solitro, both unfunded AI-FLARES members at Altec, contributed to the software verification, algorithm validation and dissemination of results.

AI-FLARES Work Packages

AI-FLARES was made of the following three scientific work packages (WPs):
- WP2100 (leader: F Benvenuto): desaturation of EUV maps recorded by SDO/AIA by means of inverse diffraction methods.
- WP3100 (leader: A M Massone): imaging spectroscopy at high-energy regimes for solar flares.
- WP4100 (leader: C Campi): machine and deep learning for flare forecasting from SDO/HMI magnetograms of the full solar disk.

A further technological WP5100 (leader: A M Massone) was devoted to the construction of computational pipelines for the analysis of flares-related data. Finally, WP1200 (leader: M Piana) implemented the coordination and dissemination efforts for the project.

AI-FLARES criticalities

AI-FLARES kick-off was at the end of 2019 and after some weeks the world entered the pandemic nightmare, which of course had significant impacts on the implementation of research projects at all levels and all around the world. As far as the specific case of AI-FLARES is concerned, these impacts have been mitigated by two facts. First, despite the pandemic-related restrictions, Solar Orbiter started its trip to the Sun on February 2020 and STIX, on-board Solar Orbiter, began sending us high-energy visibilities rather soon, in September of the same year. As a result, AI-FLARES activity on hard X-ray imaging spectroscopy could exploit not only the well-established RHESSI data, but also the exciting new measurements provided by the new visibility-based instrument, which is part of the ESA cluster. The second aspect that significantly mitigated the impact of lock-downs on AI-FLARES activities was the notable collaborative mood that characterized our team. Indeed, starting from March 2020, we set up on-line meetings on a weekly basis, devoted to discuss computation heliophysics issues addressed within our (extended) research group and AI-FLARES science was at the core of essentially all such meetings.

Therefore, we can conclude that the main critical issue concerned with AI-FLARES at a scientific level has been the fact that the dissemination of results at the main solar physics and space weather forums was slowed down in the beginning, and then gradually postponed toward the end of the project activities. At a more technical level, we have also to note that, in the course of the project, one of the team leaders (C Campi) moved from a researcher position at the Università di Padova to an Associate Professor position at the Università di Genova. However, this change did not impact at all the scientific effectiveness of the whole AI-FLARES collaboration.

AI-FLARES results

We believe that AI-FLARES accomplished significant scientific results in all the three topics that represented the core of its activity. We now briefly overview such results, emphasizing the ones that probably represent the most notable research outcomes of the project.

Results concerning hard X-ray imaging spectroscopy

In this topic, AI-FLARES results have been of three kinds. We formulated the mathematical model for the image formation process of STIX visibilities and contributed to the calibration process for all thirty STIX collimators devoted to imaging. We then developed several image reconstruction methods able to represent in the image space the information contained in the hard X-ray visibilities recorded by either RHESSI or STIX. Specifically, we have formulated, implemented and validated:

- A maximum entropy method, in which the solution is constrained to have positive entries and total flux equal to an a priori estimate.
- An interpolation/extrapolation method based on feature augmentation and on the use of Variably Scaled Kernels (VSKs).
- A parametric imaging method that works for both a partial information on the visibility set (when just the visibility amplitudes are provided by the instrument) and visibilities recorded by fully calibrated collimators.
- A multi-scale version of the CLEAN deconvolution algorithm that has been implemented for RHESSI and whose implementation for STIX is under construction.

Finally, and probably more importantly, as part of the RHESSI legacy we formulated and implemented a regularization method that is able to reconstruct maps whose pixel content is proportional to the average flux of the electrons accelerated along the magnetic field lines from the corona down to the chromosphere. The nicest aspect of this methodological approach is that it is able to provided electron maps that are constrained to vary in a smooth way along the spectral direction and that can be projected back to the photon domain to produce photon maps that are in turn regularized across energy. This approach may represent an important step to a full interpretation of STIX data within the framework of imaging spectroscopy and, as preliminarily shown in Figure 1, may provide a crucial tool for the understanding of electron acceleration mechanisms during solar flares.

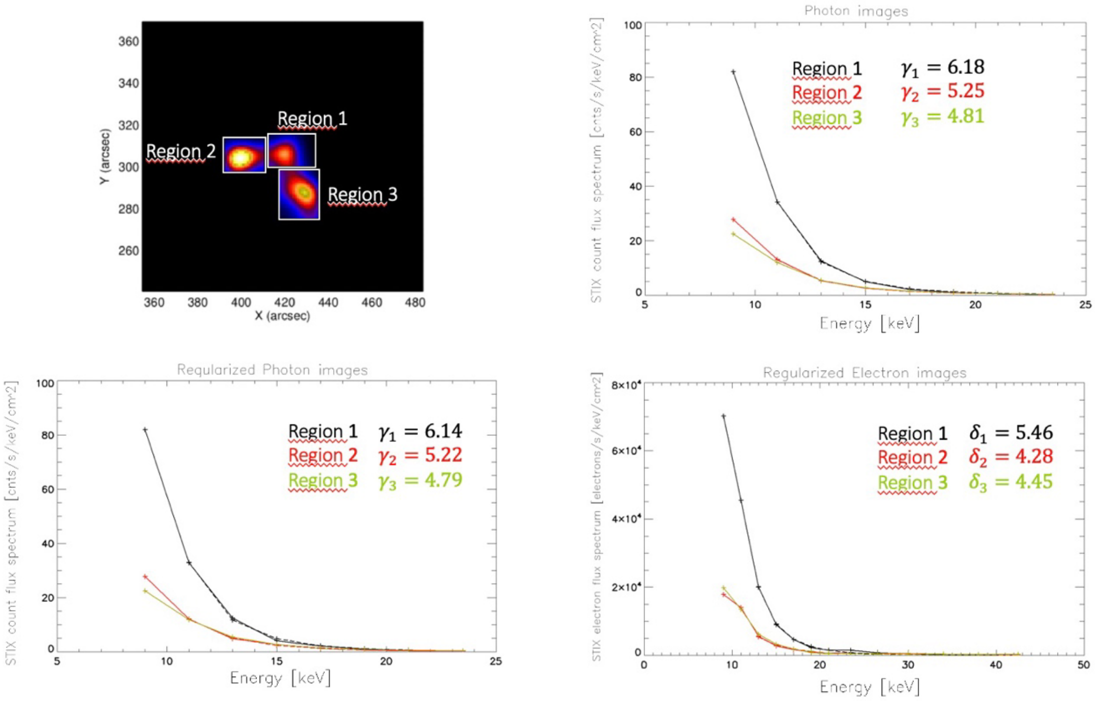

Figure 1: spatially resolved imaging spectroscopy from STIX data

Results concerning EUV imaging

EUV measurements recorded in correspondence with intense solar flares are almost systematically affected by saturation. After the launch of SDO/AIA, the desaturation of EUV images has become a big data issue, since AIA has been providing more the 10^5 frames per year since February 2010. AI-FLARES introduced two novel desaturation methods. The 'SE-DESAT' pipeline is based essentially on three ingredients: the inversion of the diffraction fringes to recover the information in image core associated to primary saturation, the encoding of a sparsity constraint within the inverse diffraction process, and the exploitation of the Poisson nature of the input data. Then, the 'adaptive SE-DESAT' pipeline introduces weights depending on the shape of the saturated region. An example of results provided by the two pipelines is illustrated in Figure 2.

We point out that the availability of this desaturation pipeline has currently two important consequences. First, scientists working in the STIX community are used to superimpose the reconstructed hard X-ray sources on the high-resolution AIA maps, in order to improve the interpretation of the morphological characteristics of the emission. We are currently including the desaturation pipeline into a more comprehensive pipeline that is able to realize such superposition in a completely automated fashion. Second, AI-FLARES people are currently involved in a NASA project for nowcasting solar flares starting from AIA information. Once again, image desaturation will be a crucial pre-processing step for the realization of a prediction approach that will apply machine learning to de-saturated EUV maps.

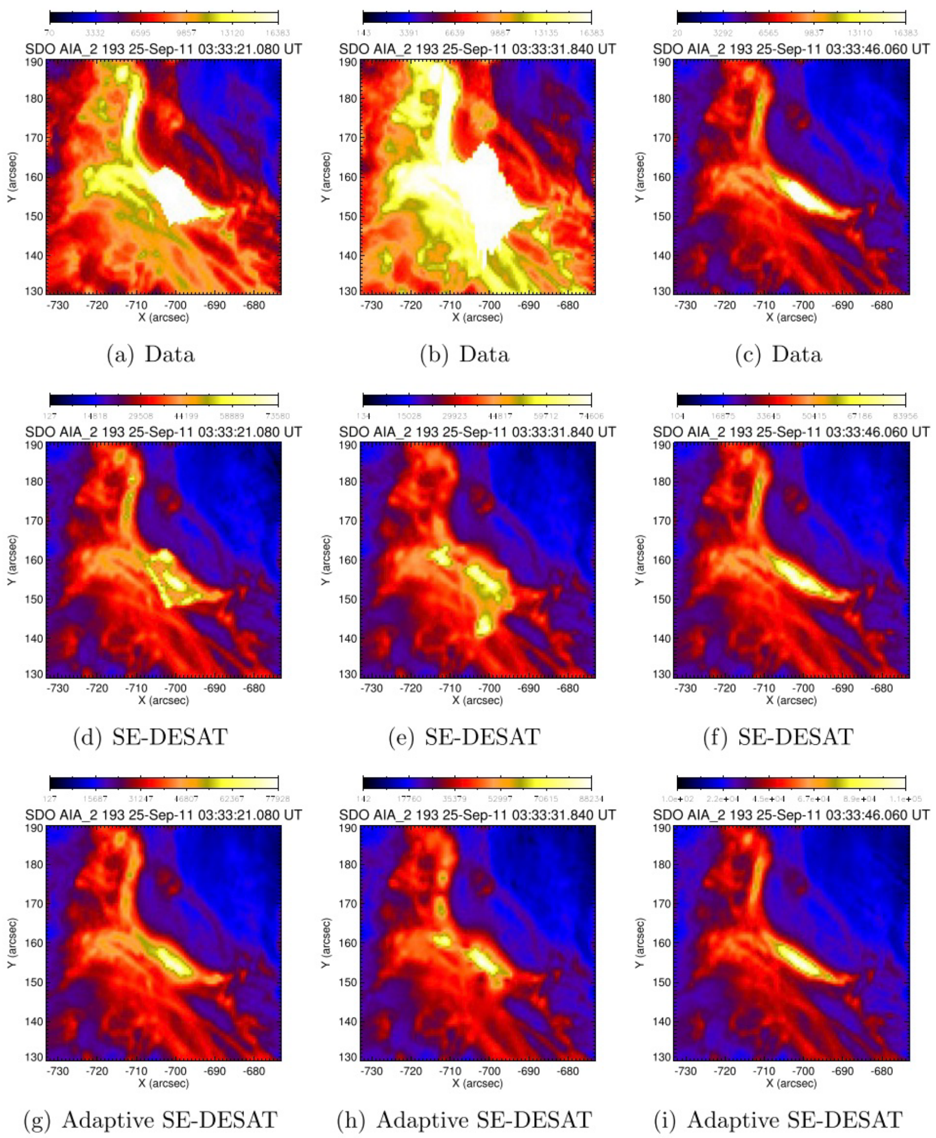

Figure 2: outcomes of the 'SE-DESAT' and 'adaprive SE-DESAT' AI-FLARES pipelines

Results concerning flare forecasting

This topic has been addressed by AI-FLARES according to two perspectives. We first studied how to identify active region (AR) descriptors that mostly impact the prediction effectiveness of machine learning data. Specifically, using sparsity-enhancing approaches we were able to prove that:

- Very few AR descriptors are really effective in the forecasting process and these descriptors are very robust, independently of the regularization network used and of other experimental aspects like the issuing times considered in the training set.
- The Ising energy seems to systematically play a notable predictive role, specifically in the case of the forecasting of particularly intense flaring storms.
- The computation of innovative topological descriptors can represent a way to improve the skill scores associated to feature-based machine learning algorithms.

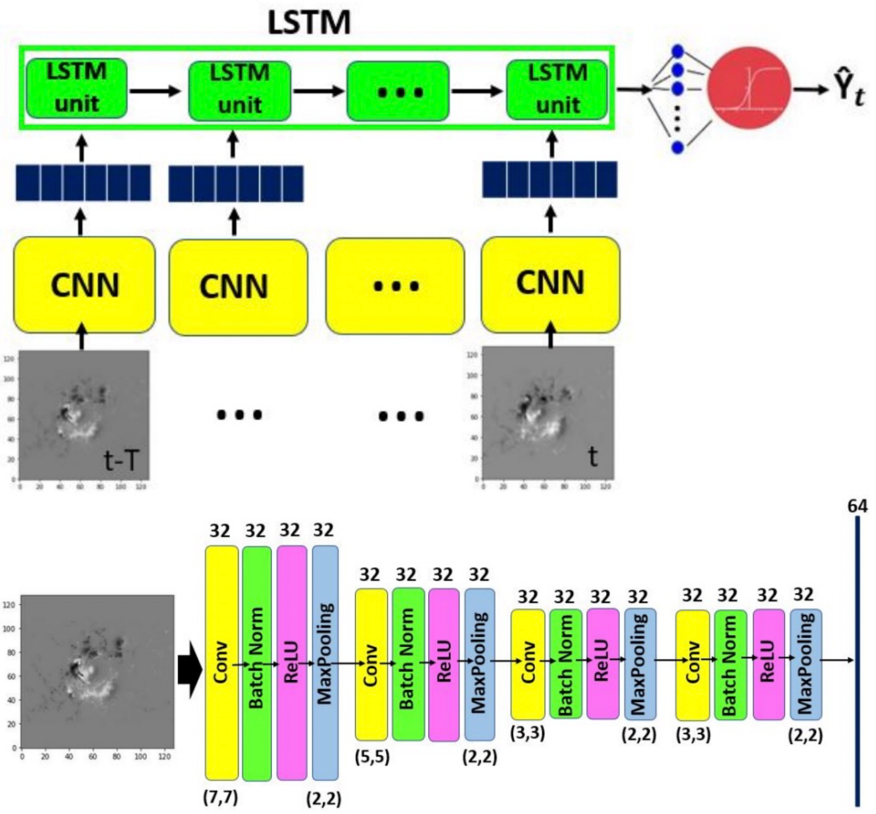

Figure 3: the AI-FLARES deep learning pipeline for flare forecasting

The second perspective was the development of deep learning networks able to provide a notable prediction improvement in the difficult game of solar flare forecasting. In this context, we think that the main result of AI-FLARES has been the implementation of a pipeline that, for the first time, utilizes videos of HMI frames as input data and that, for the first time, account for an appropriate balancing of different data sample types in the training and validation phases of the neural network. In our view, this pipeline, which is illustrated in Figure 3, can be considered an important step toward the path of operational flare forecasting by means of artificial intelligence tools.

As a final comment, we point out that AI-FLARES provided contributions also in the methodological field related to machine and deep learning research. In particular, during this project two theoretical ideas have been conceived and formulated. The first one is about the use of probabilistic score-oriented loss functions in the training phase for the neural network; the second one is about the use of value-weighted skill scores for the performance assessment of both machine and deep learning. These two methodological tools have been utilized in most networks designed for the flare forecasting approaches developed within AI-FLARES.

AI-FLARES deliverables

AI-FLARES has deployed deliverables of three kinds: papers published in refereed international journals, talks at conferences and workshops, and computational pipelines.

AI-FLARES papers

From the kick-off of the project, we have either published or submitted the following 21 papers (around five per year):

1. Massa P, Hurford G, Volpara A, Kuhar M, Battaglia AF, Xiao H, Casadei D, Perracchione E, Garbarino S, Guastavino S, Collier H. STIX imaging I--Concept. arXiv preprint arXiv:2303.02485. 2023 Mar 4.
2. Volpara A, Piana M, Massone AM. Multi-scale CLEAN in hard X-ray solar imaging. arXiv preprint arXiv:2303.16272. 2023 Mar 28.
3. Marchetti F, Perracchione E, Volpara A, Massone AM, De Marchi S, Piana M. Mapped Variably Scaled Kernels: Applications to Solar Imaging. arXiv preprint arXiv:2304.00975. 2023 Apr 3.
4. Guastavino S, Marchetti F, Benvenuto F, Campi C, Piana M. Operational solar flare forecasting via video-based deep learning. arXiv preprint arXiv:2209.05128. 2022 Sep 12.
5. Stiefel M Z, Battaglia A F, Barczynski K, Volpara A, Massa P, Collier H, Schwanitz C, Tynelius S, Harra L, and Krucker S. Solar Flare Hard X-rays from the Anchor Points of an Eruptive Filament. Astronomy & Astrophysics. 2023 February; 670:A89.
6. Rodriguez L, Warmuth A, Andretta V, Mierla M, Zhukov AN, Shukhobodskaia D, Niemela A, Maharana A, West MJ, Kilpua EK, Möstl C. The Eruption of 22 April 2021 as Observed by Solar Orbiter: Continuous Magnetic Reconnection and Heating After the Impulsive Phase. Solar Physics. 2023 Jan;298(1):1.
7. Xiao H, Maloney S, Krucker S, Dickson E, Massa P, Lastufka E, Battaglia AF, Etesi L, Hochmuth N, Schuller F, Ryan DF. The data center for the X-ray spectrometer/imager STIX onboard Solar Orbiter. arXiv preprint arXiv:2302.00497. 2023 Feb 1.
8. Guastavino S, Marchetti F, Benvenuto F, Campi C, Piana M. Implementation paradigm for supervised flare forecasting studies: A deep learning application with video data. Astronomy & Astrophysics. 2022 Jun 1;662:A105.
9. Guastavino S, Piana M, Benvenuto F. Bad and good errors: value-weighted skill scores in deep ensemble learning. IEEE Transactions on Neural Networks and Learning Systems. 2022 Jul 1.
10. Marchetti F, Guastavino S, Piana M, Campi C. Score-oriented loss (sol) functions. Pattern Recognition. 2022 Dec 1;132:108913.
11. Volpara A, Massa P, Perracchione E, Battaglia AF, Garbarino S, Benvenuto F, Krucker S, Piana M, Massone AM. Forward fitting STIX visibilities. Astronomy & Astrophysics. 2022 Dec 1;668:A145.
12. Perracchione E, Massa P, Massone AM, Piana M. Visibility interpolation in solar hard x-ray imaging: application to RHESSI and STIX. The Astrophysical Journal. 2021 Oct 4;919(2):133.
13. Battaglia AF, Saqri J, Massa P, Perracchione E, Dickson EC, Xiao H, Veronig AM, Warmuth A, Battaglia M, Hurford GJ, Meuris A. STIX X-ray microflare observations during the Solar Orbiter commissioning phase. Astronomy & Astrophysics. 2021 Dec 1;656:A4.
14. Massa P, Perracchione E, Garbarino S, Battaglia AF, Benvenuto F, Piana M, Hurford G, Krucker S. Imaging from STIX visibility amplitudes. Astronomy & Astrophysics. 2021 Dec 1;656:A25.

15. Georgoulis MK, Bloomfield DS, Piana M, Massone AM, Soldati M, Gallagher PT, Pariat E, Vilmer N, Buchlin E, Baudin F, Csillaghy A. The flare likelihood and region eruption forecasting (FLARECAST) project: flare forecasting in the big data & machine learning era. Journal of Space Weather and Space Climate. 2021;11:39.
16. Cicogna D, Berrilli F, Calchetti D, Del Moro D, Giovannelli L, Benvenuto F, Campi C, Guastavino S, Piana M. Flare-forecasting algorithms based on high-gradient polarity inversion lines in active regions. The Astrophysical Journal. 2021 Jul 1;915(1):38.
17. Massa, P., Schwartz, R., Tolbert, A.K., Massone, A.M., Dennis, B.R., Piana, M. and Benvenuto, F., 2020. MEM_GE: a new maximum entropy method for image reconstruction from solar X-ray visibilities. The Astrophysical Journal, 894(1), p.46.
18. Krucker S, Hurford GJ, Grimm O, Kögl S, Gröbelbauer HP, Etesi L, Casadei D, Csillaghy A, Benz AO, Arnold NG, Molendini F. The spectrometer/telescope for imaging X-rays (STIX). Astronomy & Astrophysics. 2020 Oct 1;642:A15.
19. Benvenuto F, Campi C, Massone AM, Piana M. Machine learning as a flaring storm warning machine: Was a warning machine for the 2017 September solar flaring storm possible?. The Astrophysical Journal Letters. 2020 Nov 19;904(1):L7.
20. Guastavino S, Benvenuto F. A mathematical model for image saturation with an application to the restoration of solar images via adaptive sparse deconvolution. Inverse Problems. 2020 Dec 15;37(1):015010.
21. Perracchione E, Massone AM, Piana M. Feature augmentation for the inversion of the Fourier transform with limited data. Inverse Problems. 2021 Aug 27;37(10):105001.
22. Guastavino S, Piana M, Massone AM, Schwartz R, Benvenuto F. Desaturating SDO/AIA observations of solar flaring storms. The Astrophysical Journal. 2019 Sep 9;882(2):109.

AI-FLARES dissemination activity

The AI-FLARES dissemination activity has been significantly limited by the mandatory restrictions related to the COVID-19 pandemic. However, in the last eighteen months AI-FLARES scientists have taken part to several dissemination events. In the following we include a non-exhaustive list of such events:

1. 16th European Solar Physics Meeting, 6-10 September 2021 (online)
2. 17th European Space Weather Week, 25-29 October 2021, Glasgow, UK
3. 8th Solar Orbiter Workshop, 12-15 September 2022, Belfast, Uk
4. SPHERE Workshop, 11-15 July 2022, Windisch, Switzerland
5. STIX colocation meeting, 28 March - 1 April 2022, Windisch, Switzerland
6. 3rd SWATNET Workshop, 29-30 September 2022, Athens, Greece
7. 18th European Space Weather Week, 24-28 October 2022, Zagreb, Croatia
8. STIX colocation meeting, 14-18 November 2022, Windisch, Switzerland
9. ASI 'Science with Current and Future Solar Physics Missions Workshop', 1-3 February 2023, Rome, Italy
10. IM-AASI Workshop, 20-24 February 2023, Bernried, Germany
11. STIX colocation meeting, 27-28 March 2023, Windisch, Switzerland
12. STIX Meeting, April 11-13 2023, Prague, Czech Republic
13. MCH23, 19-21 April 2023, Sofia, Bulgaria
14. EGU23, 23-28 April 2023, Vienna Austria

AI-FLARES software tools

The computational pipelines implemented within the AI-FLARES framework are of two kinds: pipelines already included within the paths related to NASA and ESA missions; stand-alone pipelines included in the AI-FLARES gihthub repository. We now list these pipelines together with the corresponding links.

Pipelines included in missions' trees:

- SE-DESAT (desaturation pipeline release 1.0): https://hesperia.gsfc.nasa.gov/ssw/packages/desat/idl/desat_gen__define.pro
  https://hesperia.gsfc.nasa.gov/ssw/packages/desat/idl/desat_pril__define.pro
  https://hesperia.gsfc.nasa.gov/ssw/packages/desat/idl/dst_fit__define.pro
  https://hesperia.gsfc.nasa.gov/ssw/packages/desat/idl/dst_strpril__define.pro
  https://hesperia.gsfc.nasa.gov/ssw/packages/desat/idl/main_desat_pril_test.pro
- MEM_GE (maximum entropy for RHESSI and STIX):
  - https://hesperia.gsfc.nasa.gov/ssw/gen/idl/image/vis/mem_ge.pro
  - https://hesperia.gsfc.nasa.gov/ssw/gen/idl/image/vis/mem_ge_fb.pro
  - https://hesperia.gsfc.nasa.gov/ssw/gen/idl/image/vis/mem_ge_mean_visib.pro
- STIX ground software (imaging pipeline):
  - Pixel data construction routines:
    - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/pixel_data/stx_construct_pixel_data.pro
    - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/pixel_data/stx_construct_pixel_data_summed.pro
    - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/pixel_data/stx_sum_pixel_data.pro
  - Visibility construction and calibration routines:
    - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/vis/stx_calibrate_visibility.pro
    - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/vis/stx_construct_calibrated_visibility.pro
    - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/vis/stx_construct_visibility.pro
    - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/vis/stx_pixel_data_summed2visibility.pro
  - Routines for reading auxiliary fits files containing aspect information:
    - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/aux_data/stx_create_auxiliary_data.pro
  - Routines for performing coordinate transformation (for precisely locating the STIX reconstructed maps):

        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/coordinates/stx_hpc2rtn_coord.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/coordinates/stx_hpc2stx_coord.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/coordinates/stx_rtn2solo_coord.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/coordinates/stx_rtn2stx_coord.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/coordinates/stx_solo2stx_coord.pro
    - Routines for calibrating the sub-collimator transmission:
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/subcollimator/stx_grid_transmission.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/subcollimator/stx_subc_transmission.pro
    - Routines for determining the location of the flare:
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/stx_estimate_flare_location.pro
    - VIS_FWDFIT_PSO routines:
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_func_pso.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso_circle_struct_define.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso_func_makealoop.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso_loop_struct_define.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso_multiple_src_create.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso_source2map.pro

        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso_src_bifurcate.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso_src_nfurcate.pro
        - https://github.com/i4Ds/STIX-GSW/blob/master/stix/idl/processing/imaging/vis_fwdfit_pso_src_structure__define.pro

Stand-alone pipelines:

- Adaptive SE-DESAT (desaturation pipeline release 2.0): https://github.com/theMIDAgroup/AI-FLARES/tree/main/WP2100-D1/SE_DESAT_adaptive
- Flare forecasting pipelines:
    - https://github.com/theMIDAgroup/AI-FLARES/tree/main/WP4100-D2/flare_forecasting_ensemble_learning
    - https://github.com/theMIDAgroup/AI-FLARES/tree/main/WP4100-D2/forecasting_solar_storm_september_2017
    - https://github.com/theMIDAgroup/AI-FLARES/tree/main/WP4100-D2/topological_descriptor_flare_forecasting
    - https://github.com/theMIDAgroup/AI-FLARES/tree/main/WP4100-D2/video_based_DL_flare_forecasting
- Imaging spectroscopy pipeline for RHESSI
    - https://github.com/theMIDAgroup/AI-FLARES/tree/main/WP3100-D1/RHESSI_VisibilityInversionSoftware
- Imaging spectroscopy pipeline for STIX:
    - https://github.com/theMIDAgroup/AI-FLARES/tree/main/WP3100-D1/STIX_VisibilityInversionSoftware
- Imaging pipelines
    - https://github.com/theMIDAgroup/AI-FLARES/tree/main/stx_uv_smooth
    - https://github.com/theMIDAgroup/AI-FLARES/blob/main/stx_uv_smooth/uv_smooth_codes/stx_uv_smooth.pro
    - https://github.com/theMIDAgroup/AI-FLARES/blob/main/stx_uv_smooth/uv_smooth_codes/stx_make_map_uv_smooth.pro
    - https://github.com/theMIDAgroup/AI-FLARES/blob/main/stx_uv_smooth/uv_smooth_codes/uv_smooth.pro
        - https://github.com/theMIDAgroup/AI-FLARES/blob/main/stx_uv_smooth/uv_smooth_codes/uv_smooth_vsk.pro
        - https://github.com/theMIDAgroup/AIFLARES/blob/main/stx_uv_smooth/uv_smooth_codes/uv_smooth_augmented_feature.pro
        - https://github.com/theMIDAgroup/AIFLARES/blob/main/stx_uv_smooth/uv_smooth_codes/uv_smooth_vsk.pro

- https://github.com/theMIDAgroup/AI-FLARES/blob/main/stx_uv_smooth/uv_smooth_codes/matern_kernel_interp.pro
- https://github.com/theMIDAgroup/AI-FLARES/blob/main/stx_uv_smooth/uv_smooth_codes/distance_matrix.pro

Michele Piana
MIDA, Dipartimento di Matematica, Università di Genova
INAF - Osservatorio Astrofisico di Torino