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Evolution of Data-Driven Disruption Prediction: from Machine Learning to Deep Learning

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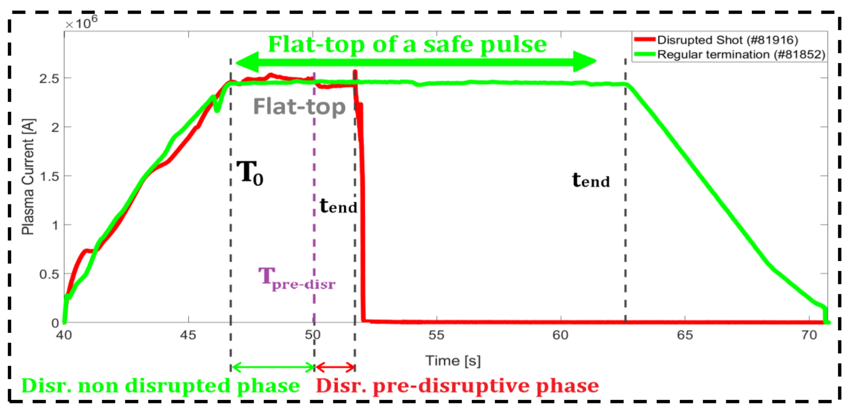
*See J. Mailloux et al. 2022 (https://doi.org/10.1088/1741-4326/ac47b4) for the JET contributors

Abstract

In view of the future high power nuclear fusion experiments, the early identification of disruptions is a mandatory requirement, and presently the main goal is moving from the disruption mitigation to disruption avoidance and control. In this work, the authors describe the evolution of the disruption predictors to overcome the inherent limitations of the data-driven approach. In [1], a Generative Topographic Mapping maps the high dimensional plasma operational space in a 2D map where different disruption risk can be easily identified. Tracking the discharge evolution on the map, the chain of events leading a disruption is followed. One of the key challenges to obtain a performing ML predictor is to identify the disrupted phase of the disrupted discharges. To meet this need, a statistical approach has been proposed in [2], which automatically detects the off-normal behavior of the plasma in a disruption. Another critical phase of ML approaches is the extraction of informative features from multidimensional diagnostics, such as plasma profiles, which have proved essential for achieving high performance. In [1], profile information have been synthesized into 0D signals. In [3] instead, a deep learning prediction model, based on deep Convolutional Neural Network (CNN), has been implemented, where plasma profiles are processed as predictor input images.

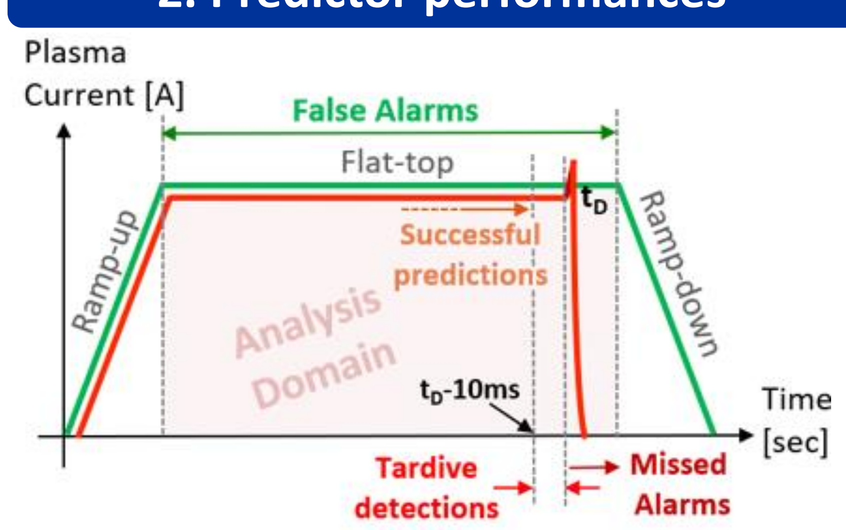
1. Sample labelling for ML training



- ✓ Non-disrupted samples: from safe pulses
- ✓ Disrupted samples: from the pre-disruptive phase of disruptions[1-3]

- t_{end} : minimum time between the TQ and DMV trigger
- T_0 is the first X-point
- $T_{pre-disr}$ defines the pre-disruptive phase length

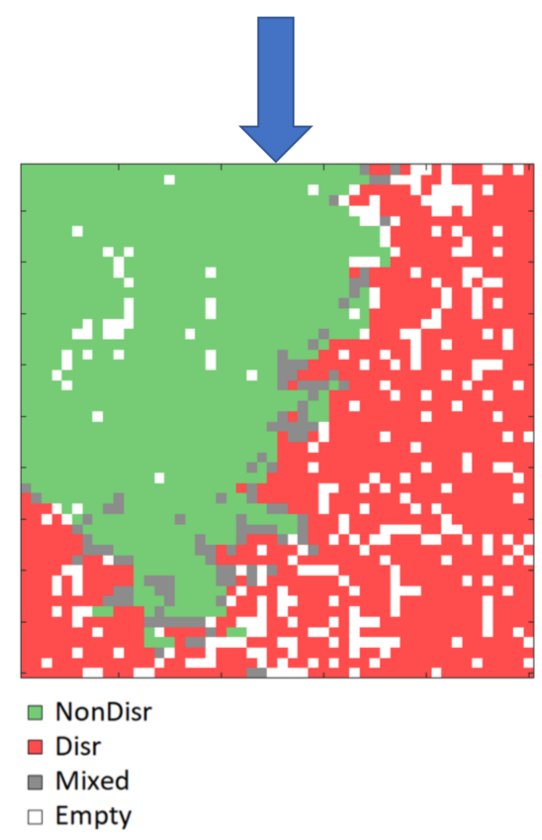
2. Predictor performances

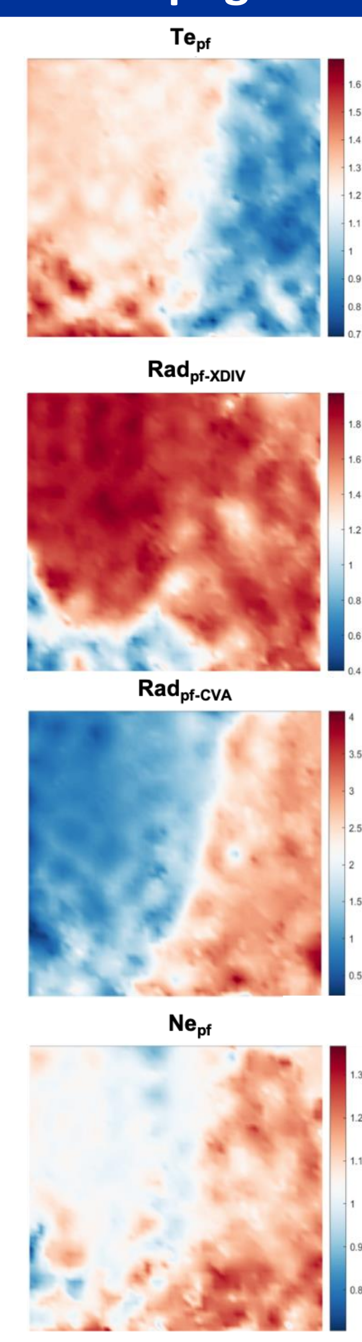


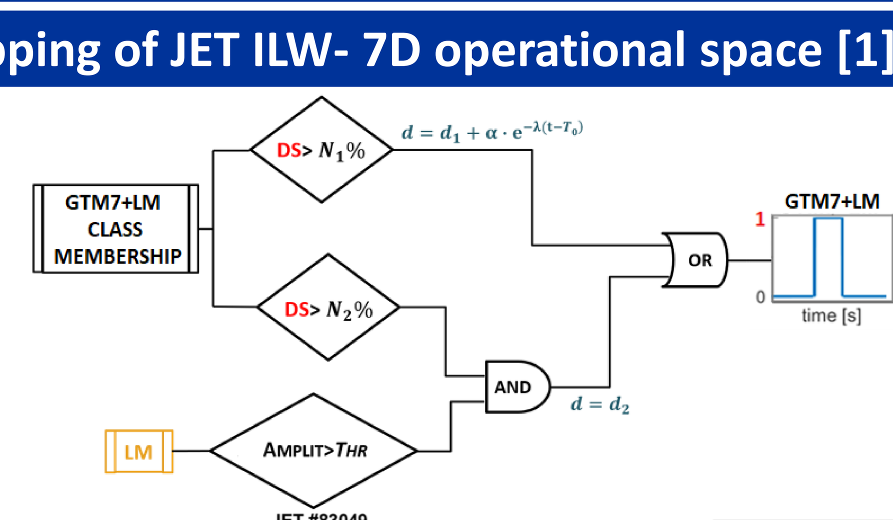
3. Generative Topografic Mapping of JET ILW- 7D operational space [1]

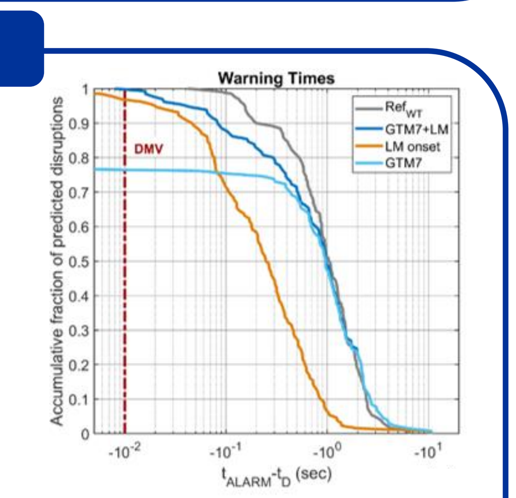
Table 1. Lists the considered parameters.

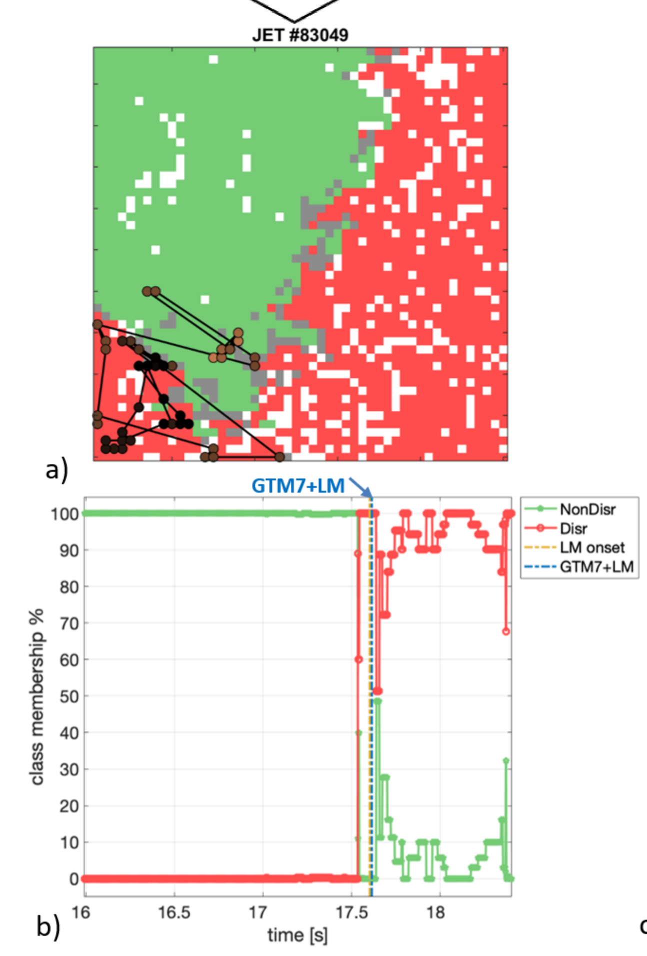
Parameter name	Acronym
Peaking factor of temperature	Te_{pf}
Peaking factor of electron density	Ne_{pf}
Peaking factor of the radiation (excluding the contribution of the X-point/divertor region)	$Rad_{pf\text{-}CVA}$
Peaking factor of the radiation (excluding the contribution of the core region)	$Rad_{pf\text{-}XDIV}$
Internal inductance	L_i
Fraction of the radiated power	P_{frac}
Safety factor on magnetic axis	q_{AX}

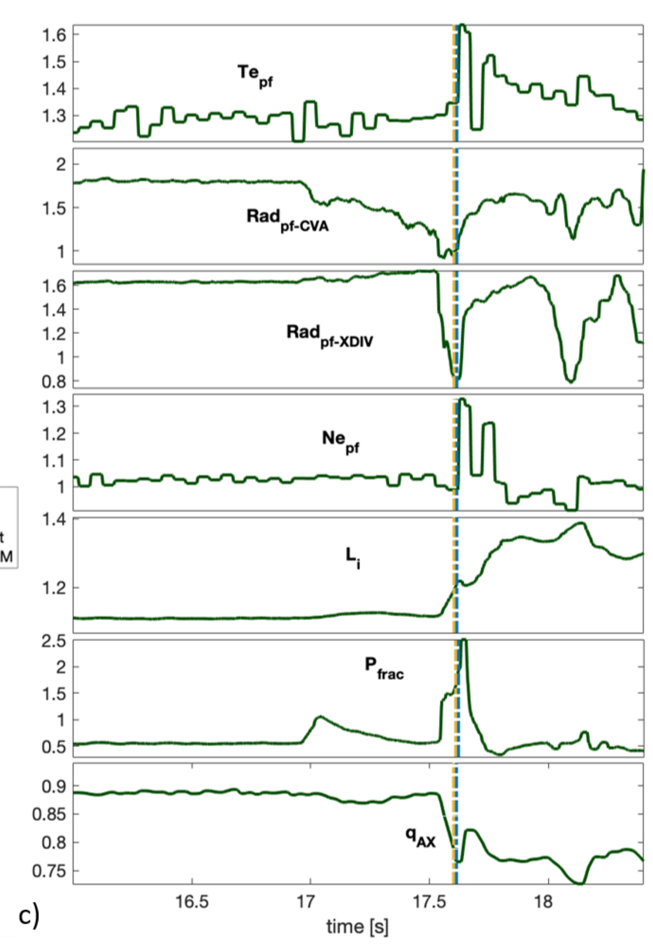








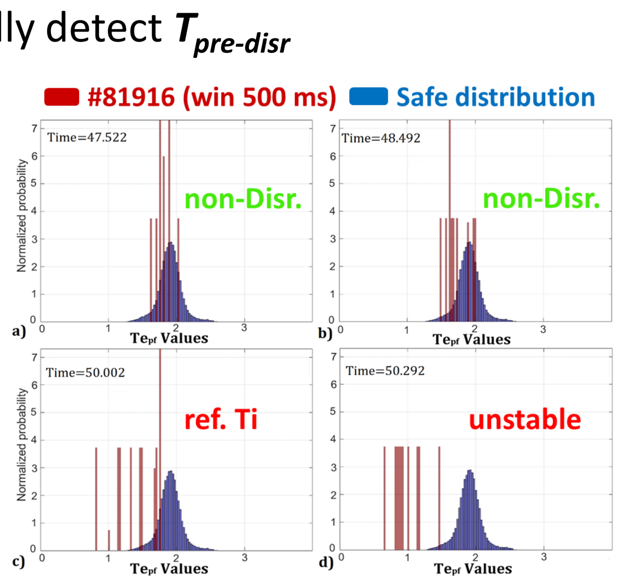


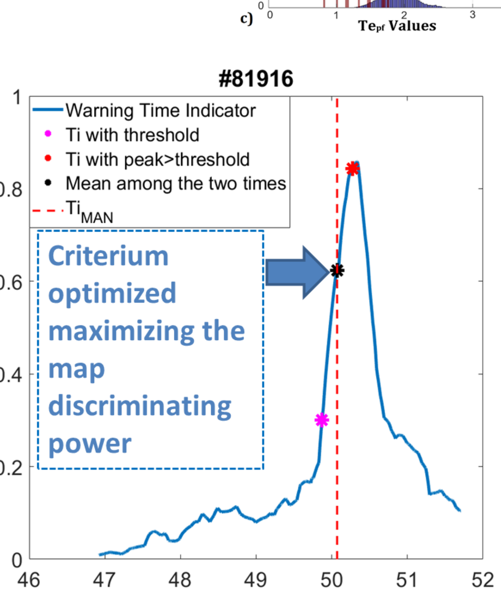


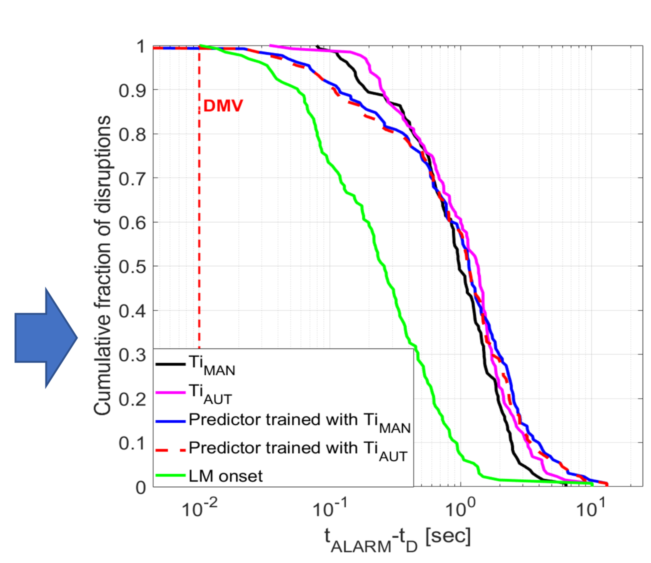
a) Projection of disruptive discharge # 83557 on the GTM. the operating point becomes darker and darker as the discharge is approaching to the final phase; b) Class member functions of the non-disrupted classes c) Time evolution of the 7 plasma parameters used to build the GTM

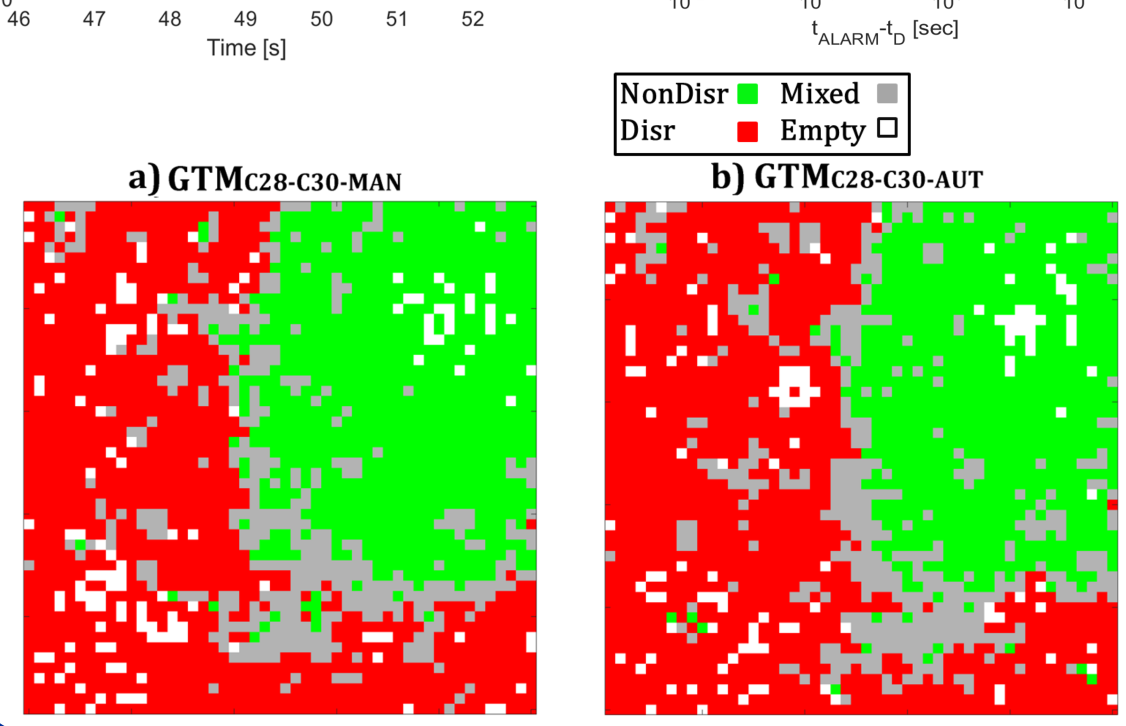
4. $T_{pre-disr}$ automatic identification [2]

An indicator obtained comparing the parameter distributions between safe and disrupted pulses has been developed to automatically detect $T_{pre-disr}$





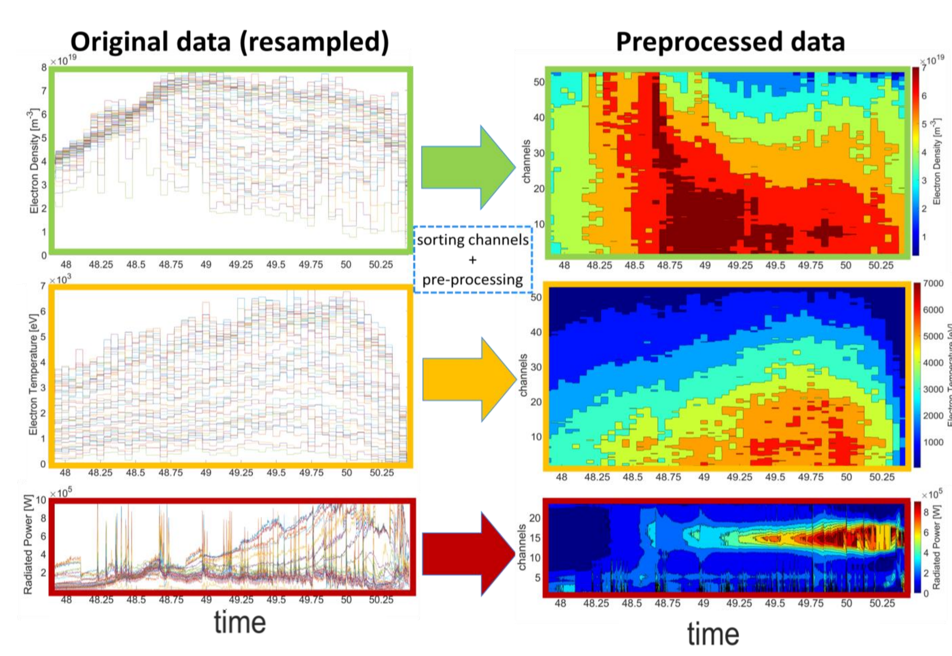


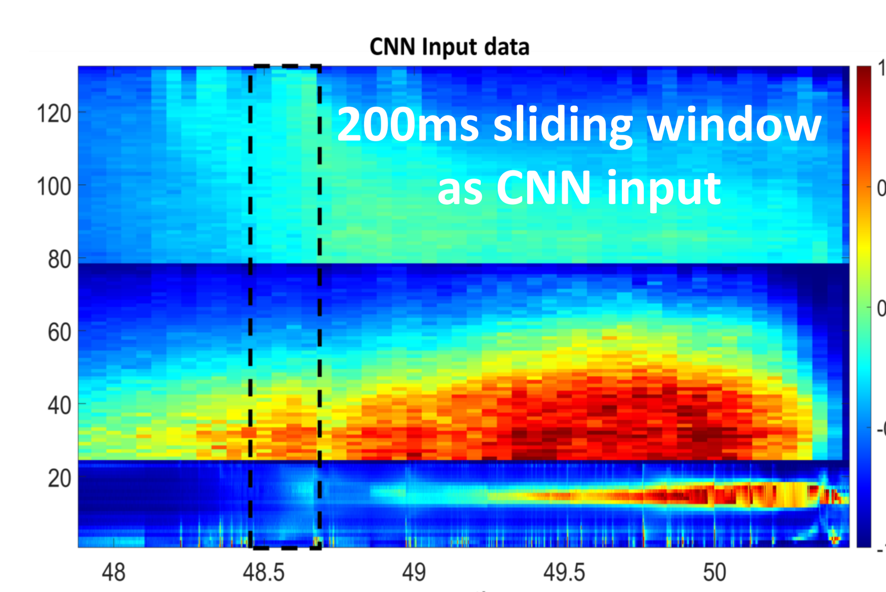


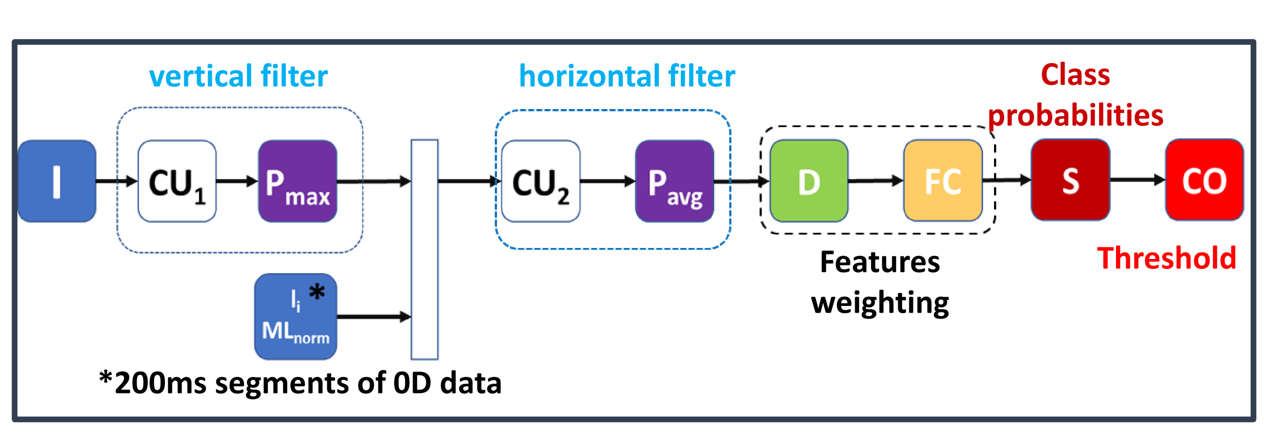
5. CNN predictor [3]

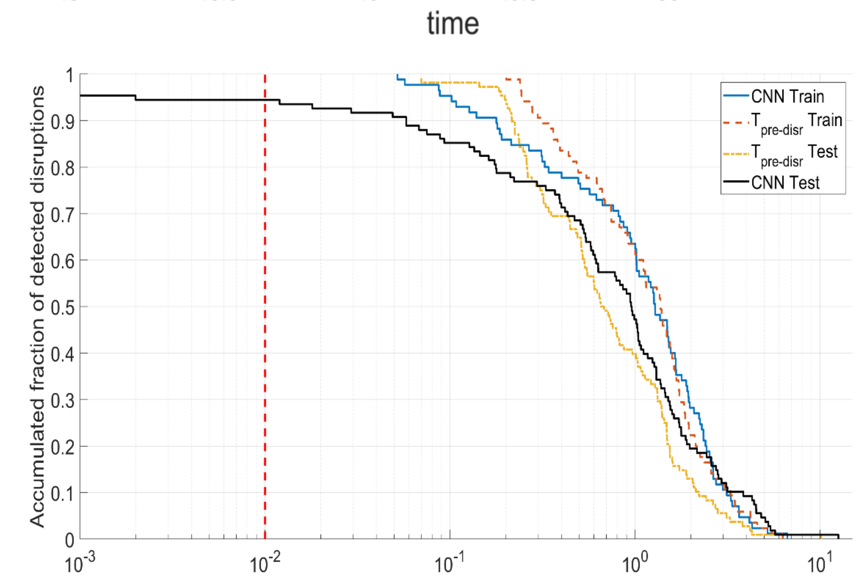
Peaking factors [1]:
- Are defined heuristically
- Lose information as they average values along the plasma profile

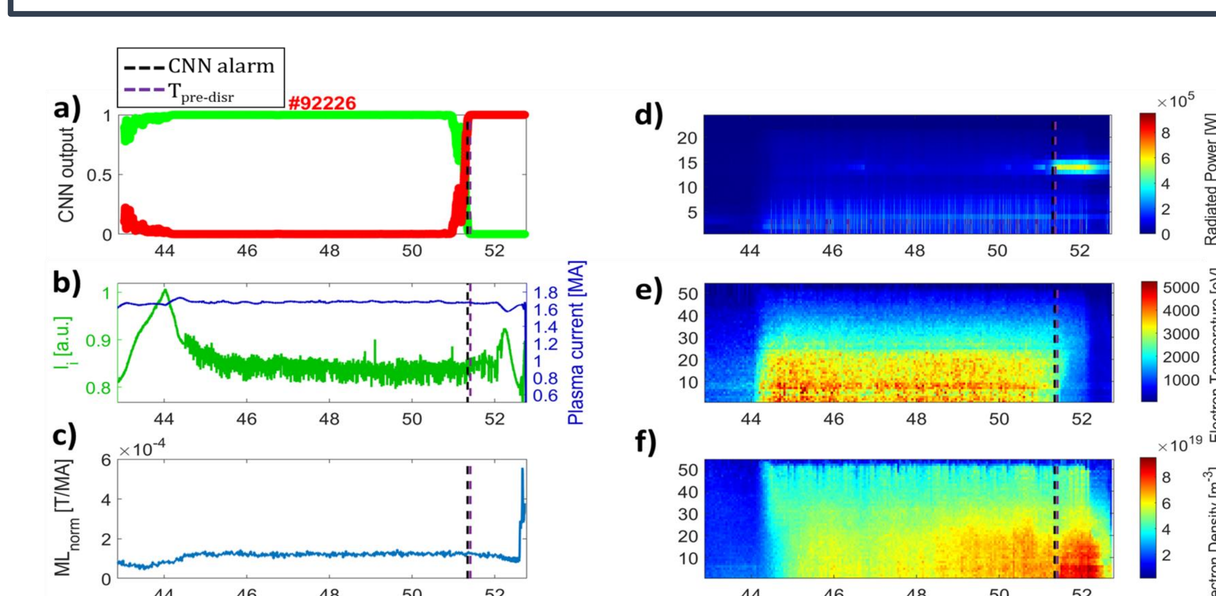
Spatiotemporal data:
- Encode spatiotemporal information
- No heuristic definition
- Report every values along the plasma profile











conclusions

The CNN performance is better than the GTM one, reaching, on the test set, about 93% of SPs, 4% of FAs, and alarm times suitable for avoidance actions. The modularity of the CNN allows the introduction of additional 2D and 1D signals from, for example, Fast Visible Cameras or spectrograms from Mirnov coils.

[1] Pau A. et al, 2019, Nucl. Fusion 59 106017.
[2] Aymerich E. et al, 2021, Nucl. Fusion 61 036013.
[3] Aymerich E. et al, 2022, Nucl. Fusion 62 066005.

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