Developing Open Machine Learning Benchmarks for Tokamak Event Prediction from MAST

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As fusion research progresses toward achieving sustainable energy production, the ability to predict disruptive tokamak events such as disruptions, edge-localized modes (ELMs), and density limits becomes increasingly critical [1]. Machine learning (ML) has emerged as a promising tool to advance event prediction by leveraging vast quantities of diagnostic and operational data [2,3,4,5]. While fusion facilities are beginning to endorse open data [6, 7, 8], and several closed databases of tokamak event data have been curated [9, 10, 11], the lack of standardized, open benchmarks and data currently impedes reproducibility and the systematic comparison of machine learning algorithms in fusion research. One notable exception is recent work [12] which aims at developing a common platform for disruption prediction for multi-machine disruption studies. Different to this effort, we consider a broader range of tasks machine learning tasks.

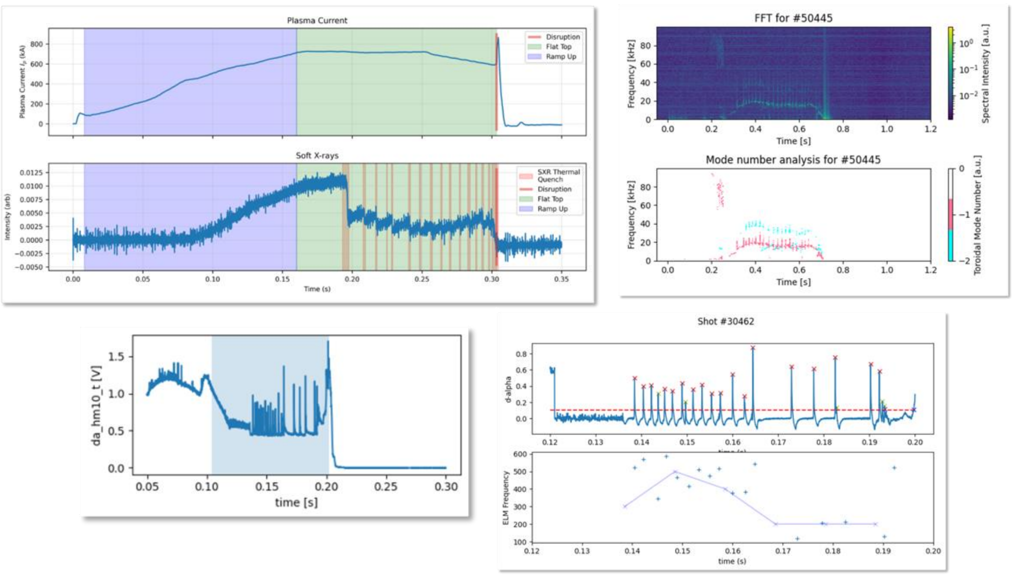

Figure 1 Example critical events curated for the MAST tokamak, including disruptions, soft x-ray thermal quenches, confinement mode, ELMs, and MHD mode numbers.

In this work, we present the development of a suite of open machine learning benchmarks designed to catalyse progress on working with tokamak data. These benchmarks encompass:

- Curated datasets from the history of the MAST experiment, structured to highlight specific challenges such as imbalanced data and multi-modal signals.
- Evaluation metrics tailored to fusion applications, including predictive accuracy and alarm time optimization.

- Reference implementations of state-of-the-art ML model provided alongside detailed documentation to ensure accessibility for fusion scientists and data practitioners.

The benchmarks are designed to align with existing community standards, to enable compatibility with experimental and synthetic diagnostic data. We demonstrate the utility of these benchmarks by evaluating models on tasks such as disruption prediction on the historical record from the MAST tokamak. Results indicate significant potential for data-driven methods to enhance tokamak operational reliability while uncovering areas requiring further methodological improvement. This initiative invites contributions from the wider community to expand the benchmarks, fostering collaboration and accelerating innovation in predictive modelling for fusion.

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