

Towards Open Machine Learning Benchmarks for Tokamak Event Prediction from MAST

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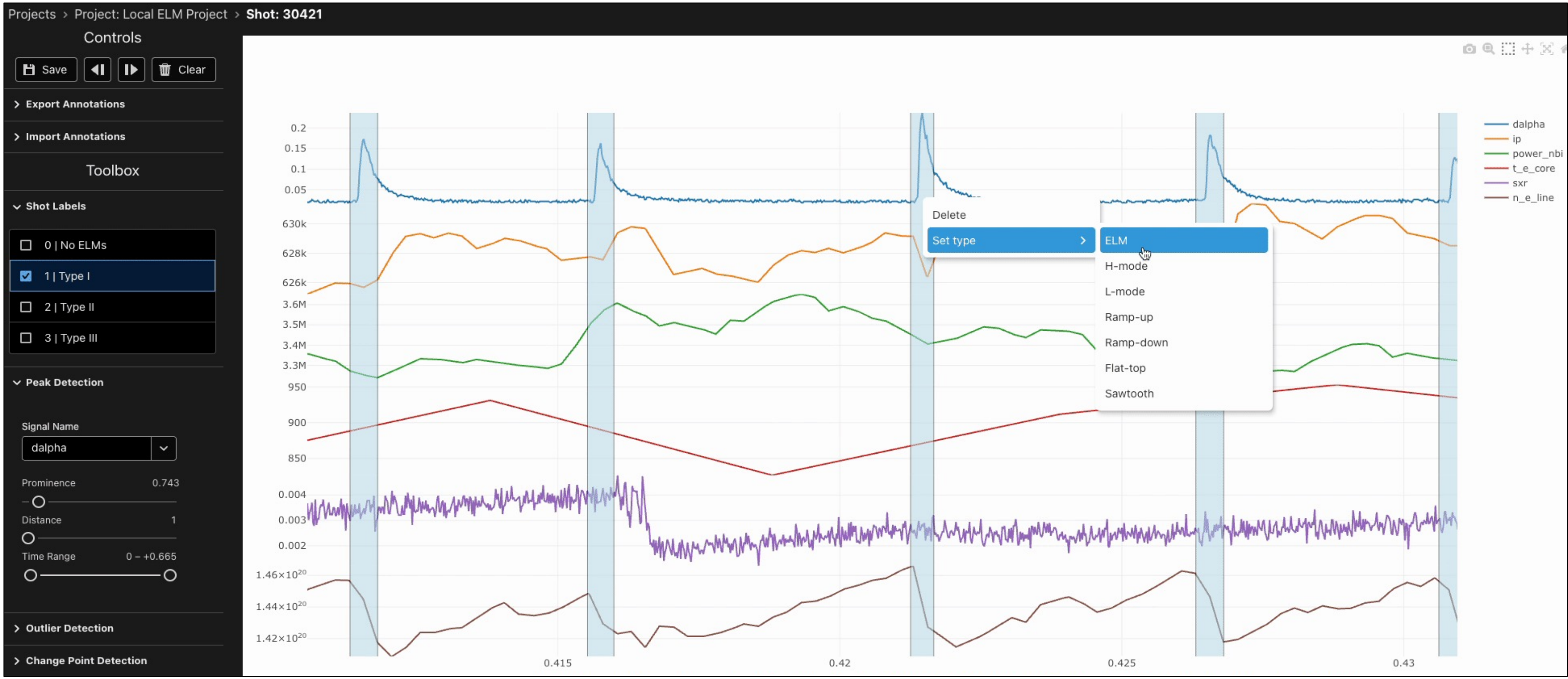
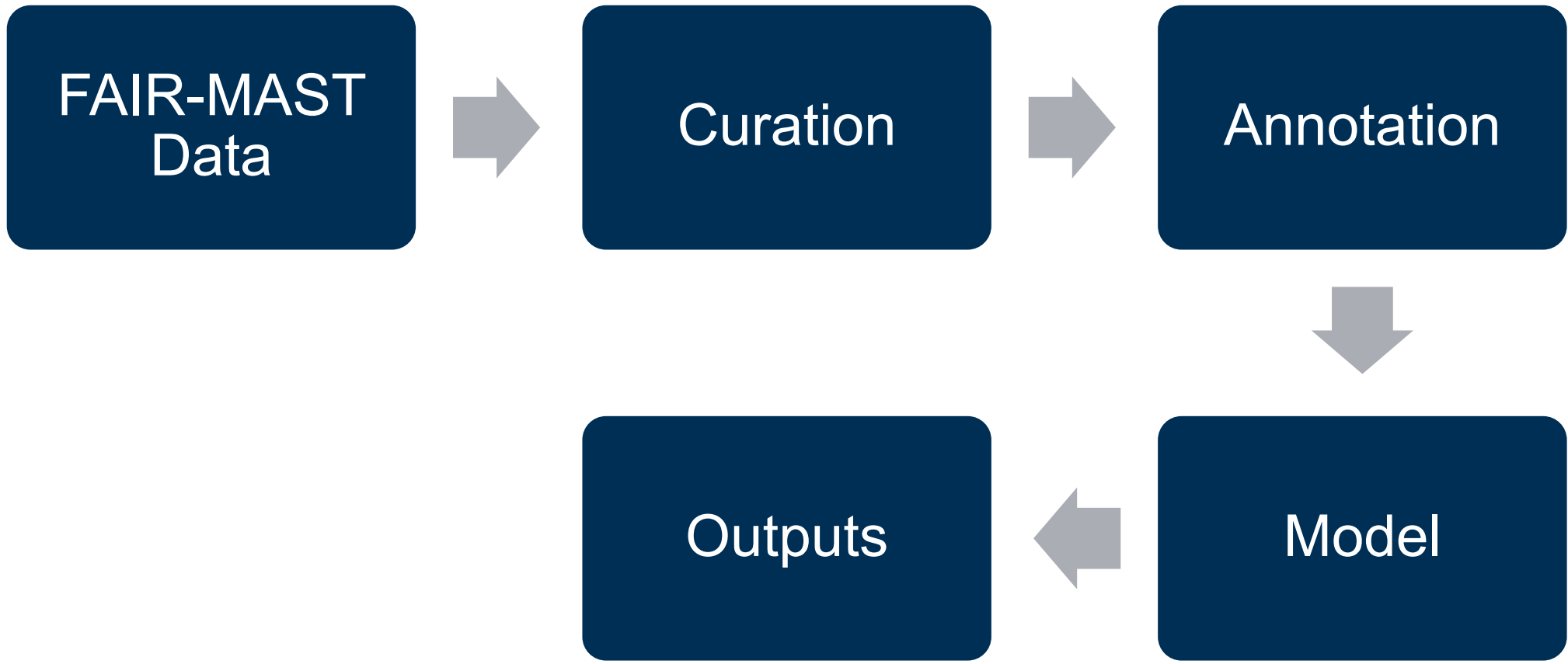
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Abstract

- Reliable prediction of disruptions, MHD modes, confinement transitions, and ELMs is essential for safe tokamak operation.
- FAIR-MAST [1,2] provides open access to MAST diagnostic data, but further processing is required to make it “AI-ready”.
- We curate annotations and develop baseline ML models for four tasks: disruption, MHD segmentation, confinement mode, and ELMs.
- Baselines provide starting points for reproducible studies and future benchmarks.

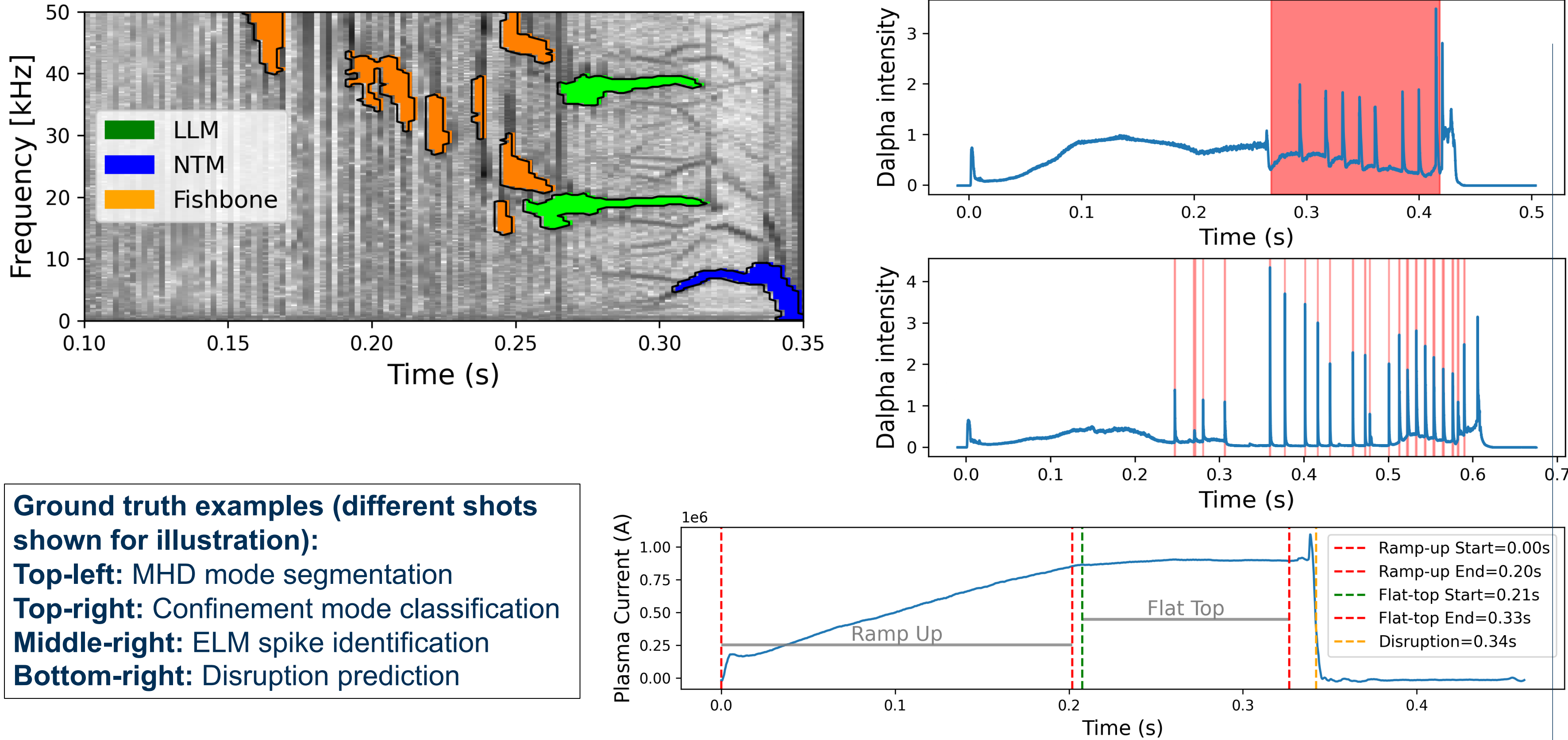
Introduction

- FAIR-MAST signals curated and prepared for ML tasks.
- Annotation process (see right).
- Label review + model feedback loop (under construction).
- Outputs: baseline models and metrics.



Disruption prediction

- Theory: Sudden loss of plasma confinement; must predict with warning time [3].
- Ground truth: Auto-detected from plasma current (417 shots).
- Model: Stacked BiLSTM with weighted sampling and sliding time window.
- Limitation: Ambiguous cases without sharp current drop remain unresolved.
- Early predictions when flat-top phase is unclear.
- Performance declines as lead time increases (tested 10/30/60 ms).



MHD mode segmentation

- Theory: Plasma instabilities (LLM, fishbones, NTMs, sawteeth) reduce performance and may trigger disruptions [4].
- Ground truth: Semi-automated spectrogram annotation from Mirnov coils (85 shots; 51 containing LLM).
- Model: Mask R-CNN with ResNet-101 backbone.
- Limitation: High-frequency structures hard to label; non-expert annotations.
- IoU is extremely low because LLMs are thin structures; small misalignments penalise overlap heavily.

Confinement mode classification

- Theory: Transition between L-mode (low confinement) and H-mode (high confinement) [5].
- Ground truth: H-mode intervals hand-labelled by expert (85 shots).
- Model: 1D U-Net with sliding time window.
- Limitation: Label boundaries may misalign by tens of ms.

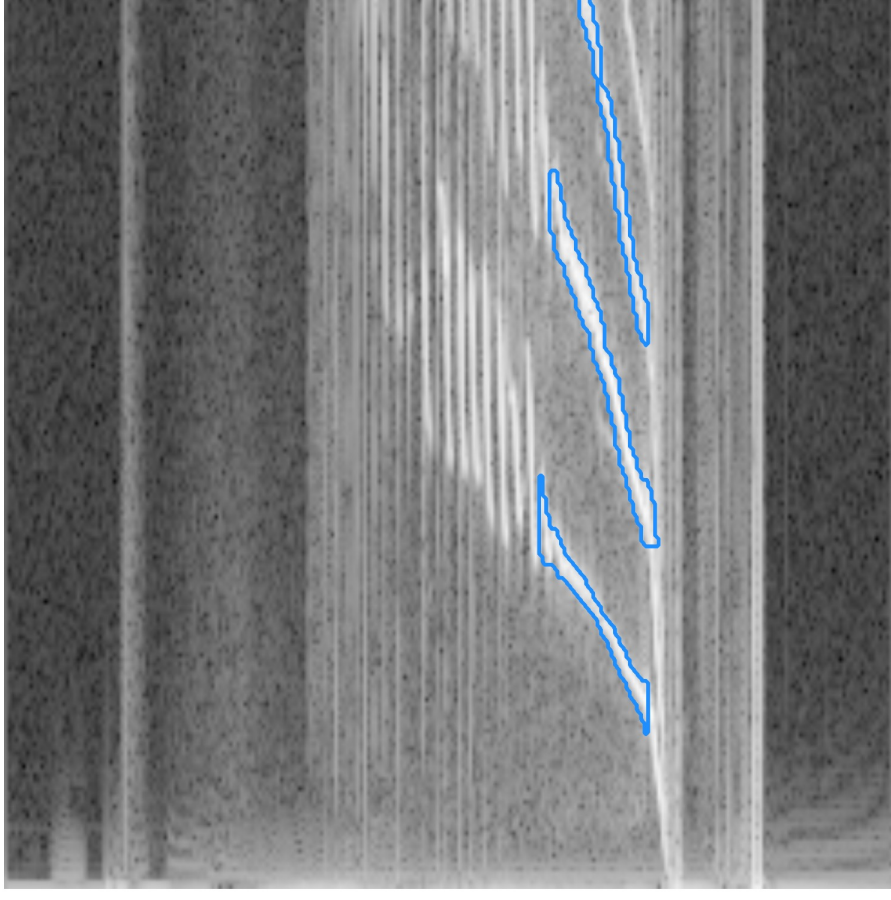
ELM spike identification

- Theory: Short bursts during H-mode, crucial for plasma-wall interaction [6].
- Ground truth: Thresholding on $D\alpha$ + manual verification (101 shots).
- Model: 1D U-Net with sliding time window.
- Limitation: Narrow spikes \rightarrow metrics sensitive to small misalignments.

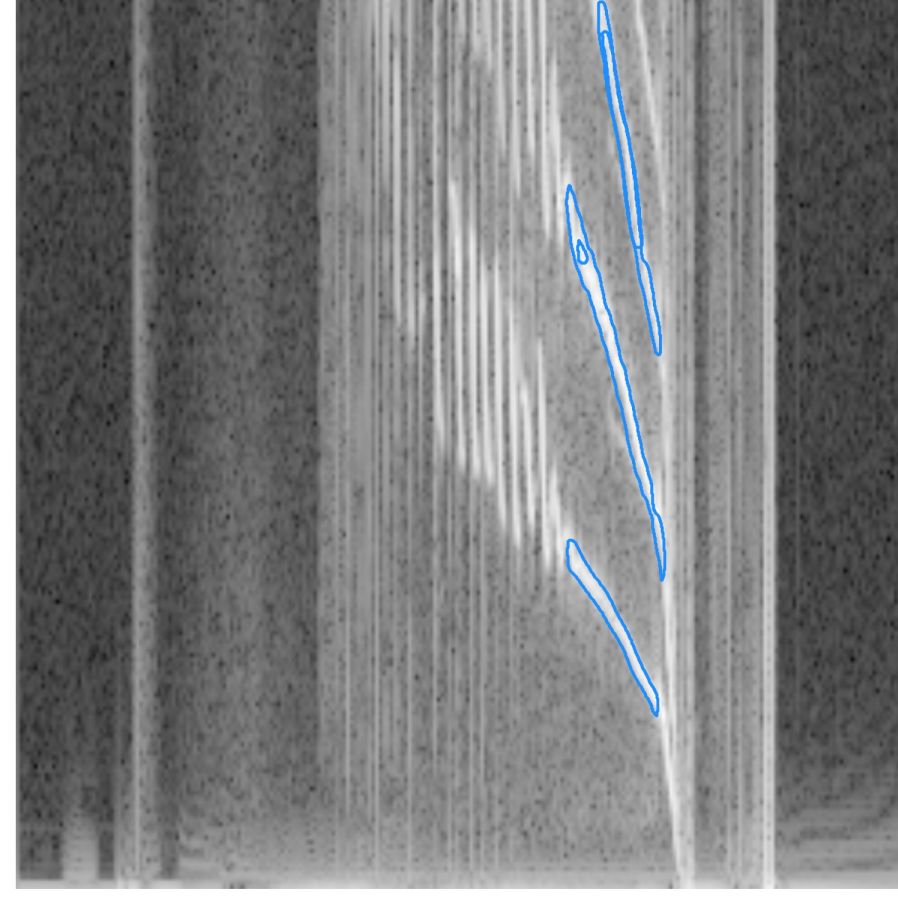
Conclusion & Future Work

- Baselines provide starting points but are not yet full benchmarks.
- Limitations include annotation noise and label misalignments.
- Current metrics do not fully capture thin/filamentary structures.
- Future work:
 - Improve label quality via review + model feedback.
 - Extend baselines towards an open benchmark suite with annotation and data tools.
 - Release datasets and models openly for community use.

Ground truth

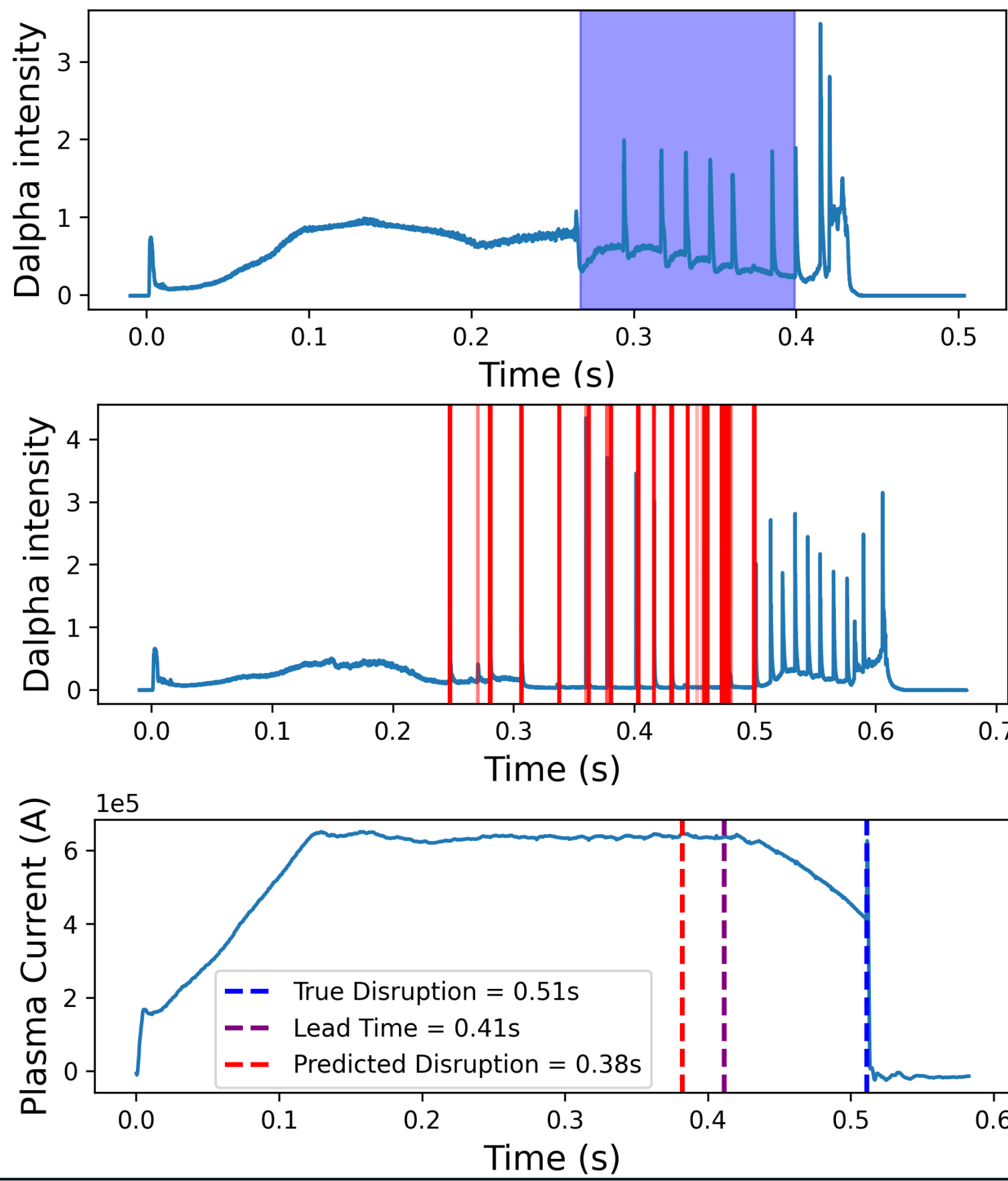


Predictions



Baseline model predictions:

- Top-left:** MHD segmentation (predicted vs labelled contours).
- Top-right:** Confinement classification (predicted H-mode interval).
- Middle-right:** ELM detection (predicted spikes in $D\alpha$).
- Bottom-right:** Disruption prediction (lead time vs true disruption).

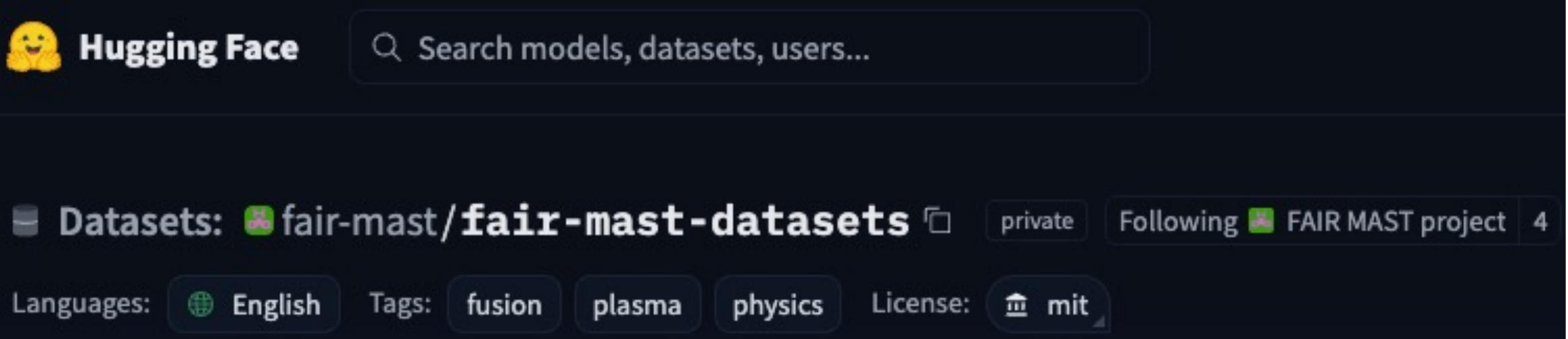


Metrics

- Accuracy omitted:** dominated by background; misleading for event detection.
- Classification - Confinement & ELMs:** Precision/Recall/F1 + ROC AUC. **Disruption:** Precision/Recall/F1 only; **ROC AUC omitted** (unreliable under extreme temporal imbalance + windowing).
- Disruption early-warning:** hit-rate 0.63; median warning 26.5 ms. Alarms earlier than 50 ms are counted as premature (not true positives).
- Segmentation (MHD):** report IoU; note it heavily penalises thin modes (LLMs).

| Task | Confinement | ELMs | MHD modes | Disruption |
|-----------|-------------|-------------|-------------|-------------|
| Precision | 0.82 ± 0.22 | 0.79 ± 0.20 | 0.75 ± 0.13 | 0.84 ± 0.07 |
| Recall | 0.83 ± 0.21 | 0.80 ± 0.20 | 0.73 ± 0.15 | 0.94 ± 0.06 |
| F1-score | 0.79 ± 0.25 | 0.78 ± 0.20 | 0.72 ± 0.10 | 0.87 ± 0.09 |
| IoU | - | - | 0.39 ± 0.01 | - |
| ROC AUC | 0.90 | 0.85 | - | - |

[1] JACKSON et al. 2024, SoftwareX.
[2] JACKSON et al. 2025, IEEE Trans. Plasma Sci.
[3] SABBAGH et al. 2023, Phys. Plasmas.
[4] THORNTON A., PhD Thesis, University of York (2011).
[5] CONNOR et al. 2000, Plasma Phys. Control. Fusion.
[6] ZOHRM et al. 1996, Plasma Phys. Control. Fusion.



AI-ready FAIR-MAST dataset (under construction)