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Plasma Disruption Prediction and Instability Events Detection in EAST Tokamak via Heterogeneous-Feature Multi-Task Learning

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ABSTRACT

- Proposed a Heterogeneous-Feature Multi-Task Learning (HFMTL) framework, for four integrated plasma-monitoring tasks: disruption prediction (DP), ELM detection, MARFE detection, and H/L-mode identification.
- HFMTL outperforms conventional multi-task and single-task learning baselines on EAST, yielding longer DP median warning time(0.480 s) and higher AUCs for H/L and MARFE, with comparable or superior performance for ELM detection. It also demonstrates better zero-shot cross-wall performance.
- HFMTL validates that correctly modeling the heterogeneous dependencies between different tasks and multi-source input signals is the key to successful multi-task learning in this domain; HFMTL thus advances integrated plasma monitoring and is promising for facilitating precursor-specific disruption avoidance.

BACKGROUND & CHALLENGES

- **Motivation:** Disruption avoidance requires not only predicting impending disruptions but also identifying their specific precursor instabilities to enable targeted control. Multi-task learning (MTL) naturally integrates these tasks, improving accuracy while reducing deployment cost.
- **Challenge:** Different tasks exhibit heterogeneous salient features (they rely on different key signals). Conventional MTL with enforced sharing induces cross-task interference, degrading performance and sometimes underperforming single-task learning (STL); this remains a central unresolved issue.

METHODS

Table 1: Dataset Overview

Task	Metric	Non-FMW			FMW
		Train	Valid	Test	Test
DP	Disrupt Shots	1984	437	477	212
	nonDisrupt Shots	4561	980	848	334
ELMs	Shots	334	66	81	138
MARFE	Shots	55	82	41	69
H/L	Shots	132	73	75	133

Dataset

- Approximately 10,000 historical EAST discharges spanning pre-upgrade non-full-metal-wall(non-FMW) and post-upgrade full-metal-wall (FMW) configurations are used.
- The non-FMW data are partitioned into training, validation, and test sets, with all FMW data used exclusively as a test set (Table 1).

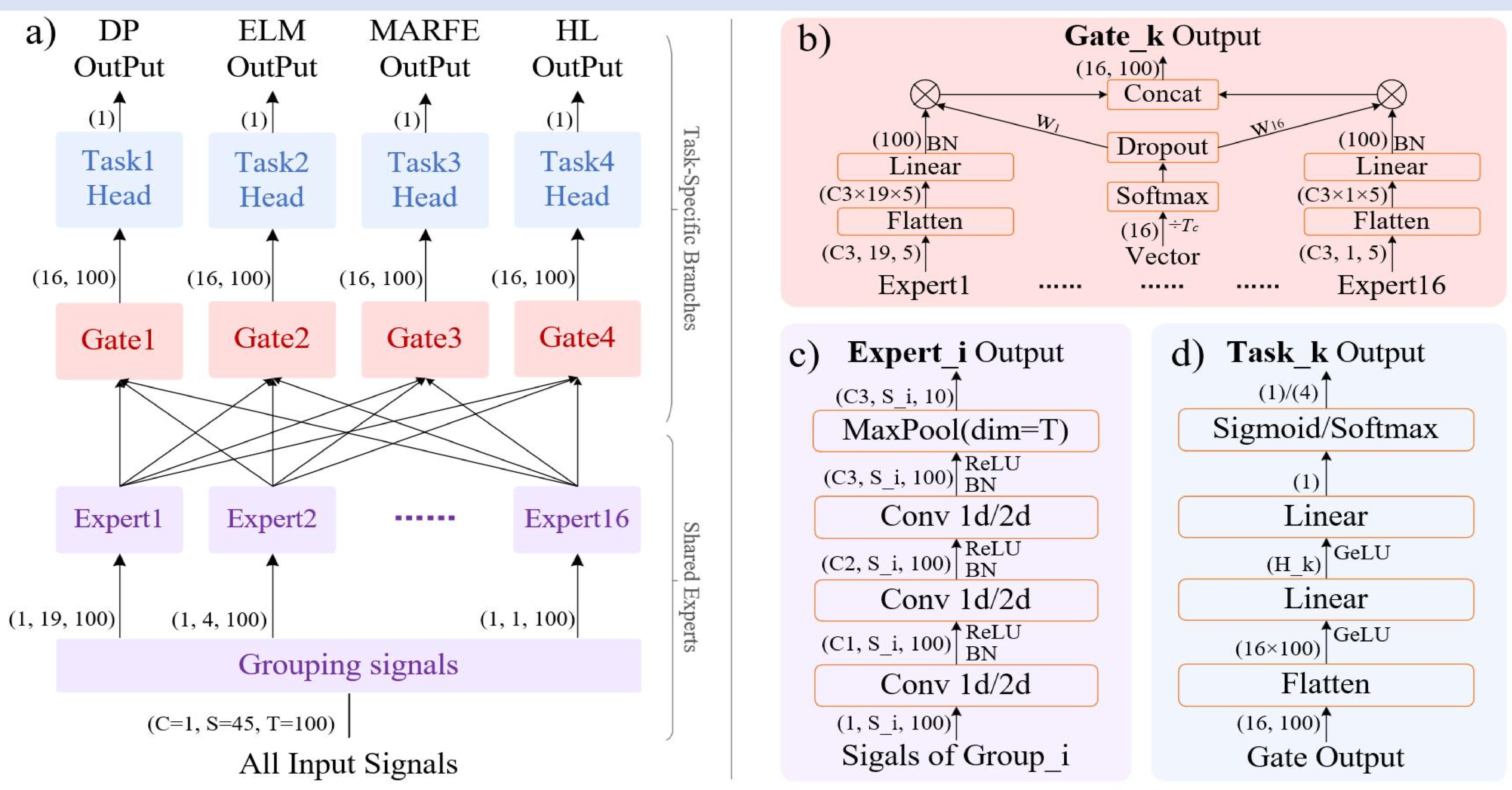

Figure 1: Schematic diagrams of the model structure.

Model Architecture

- **Structure:** Consists of expert modules, gating modules, and task heads (Fig. 1).
- **I/O:** Processes sliding-window inputs(45 signals × 100 time steps) to predict labels for four tasks.
- **Mechanism:** The 45 signals are split into 16 expert-processed groups (Table 2). For each task, a dedicated gating module adaptively weights expert outputs, filtering irrelevant signals before final prediction.
- **Initialization:** Gate weights over the 16 experts can be initialized from physics-informed priors (Table 2) and refined during training.

Ablation Test Setup

- An ablation study validates effectiveness by comparing three configurations: (1) the full HFMTL; (2) HFMTL without the gating module and (3) STL with task-specific inputs from Table 2.
- Models are trained exclusively on non-FMW data and evaluated on held-out non-FMW and FMW datasets to assess performance and cross-wall generalization (Table 1).
- All multi-task models are kept with identical parameter counts. For single-task models, the parameter count matches that of the corresponding task-specific branch in the multi-task model. All hyperparameters are tuned to optimal settings.

Table 2: Signal Groups per Task

#	Signal Group	DP	ELM	MARFE	H/L
1	Zerror	✓			
2	I_{lc}	✓			
3	$I_{p,error\ norm}$	✓			
4	kappa	✓			
5	q_{95}	✓			
6	L_i	✓			
7	D_α [a]	✓	✓		✓
8	$PXUV_{edge}$ [b]	✓	✓		✓
9	f_{GW}	✓	✓	✓	✓
10	W_{mhd}	✓	✓	✓	✓
11	I_p	✓	✓		✓
12	a_{minor}	✓	✓		✓
13	V_{loop}	✓	✓		✓
14	B_{center}	✓	✓		✓
15	$PXUV_{main}$ [c]	✓		✓	
16	POWERs [d]	✓		✓	

[a] D_α channels: L1,L2,U2,U3;
PXUV is fast bolometer at the P-port;
[b] $PXUV_{edge}$ channels: 2,6,56,58;
[c] $PXUV_{main}$ channels:9,11,13,17,19,22,24,26, 29,32,34,36,39,42,44,46,48,52,54;
[d] POWERs: P_{RAD},P_{NBI},P_{LH},P_{ICRF},P_{OHM},P_{ECRH}

OUTCOME

- Tab.3: The full HFMTL model achieves the longest median warning time (0.480 s) and the highest or joint-highest AUCs for the ELM detection, MARFE detection, and H/L identification tasks. Ablation proves the gates are essential. Removing them causes a sharp performance drop (e.g., H/L AUC: 0.999 → 0.974), confirming they prevent negative signal interference between tasks.
- Fig. 2 shows two examples: task predictions match observations, enabling ELM-free H-mode identification by combining tasks.
- Fig. 3: Gating weights over 16 signal groups. Near-zero inits stay tiny; others adapt. ELM task relies on D_α and $PXUV_{edge}$; while the H/L task additionally depends on W_{mhd}. MARFE on $PXUV_{main}$; DP on a_{minor} and $PXUV_{main}$— consistent with physical intuition.

Table 3: Results of Ablation

Model	Full HFMTL		HFMTL w/o Gate Modules		STL w/ Task-Specific Signals	
Wall Condition	Non-FMW	FMW	Non-FMW	FMW	Non-FMW	FMW
AUC_DP	0.986±0.004	0.965±0.016	0.987±0.004	0.962±0.013	0.985±0.003	0.957±0.010
Median Warning Time(s)	**0.480±0.068**	0.245±0.111	0.435±0.072	0.231±0.072	0.316±0.078	0.191±0.096
AUC_ELM	**0.996±0.001**	**0.973±0.004**	0.965±0.005	0.924±0.007	**0.995±0.003**	0.968±0.005
AUC_MARFE	**0.975±0.002**	**0.935±0.012**	0.932±0.004	0.892±0.021	0.973±0.002	0.921±0.009
AUC_H/L	**0.999±0.001**	**0.985±0.006**	0.974±0.006	0.941±0.011	0.992±0.001	0.957±0.008

Boldface uses two-sided Welch t-tests (n=20 runs with random seeds, α=0.05). "±" is the standard deviation. Boldface indicates the best-performing model in each row. If multiple models are statistically indistinguishable from the best (p ≥ 0.05), they are also bolded

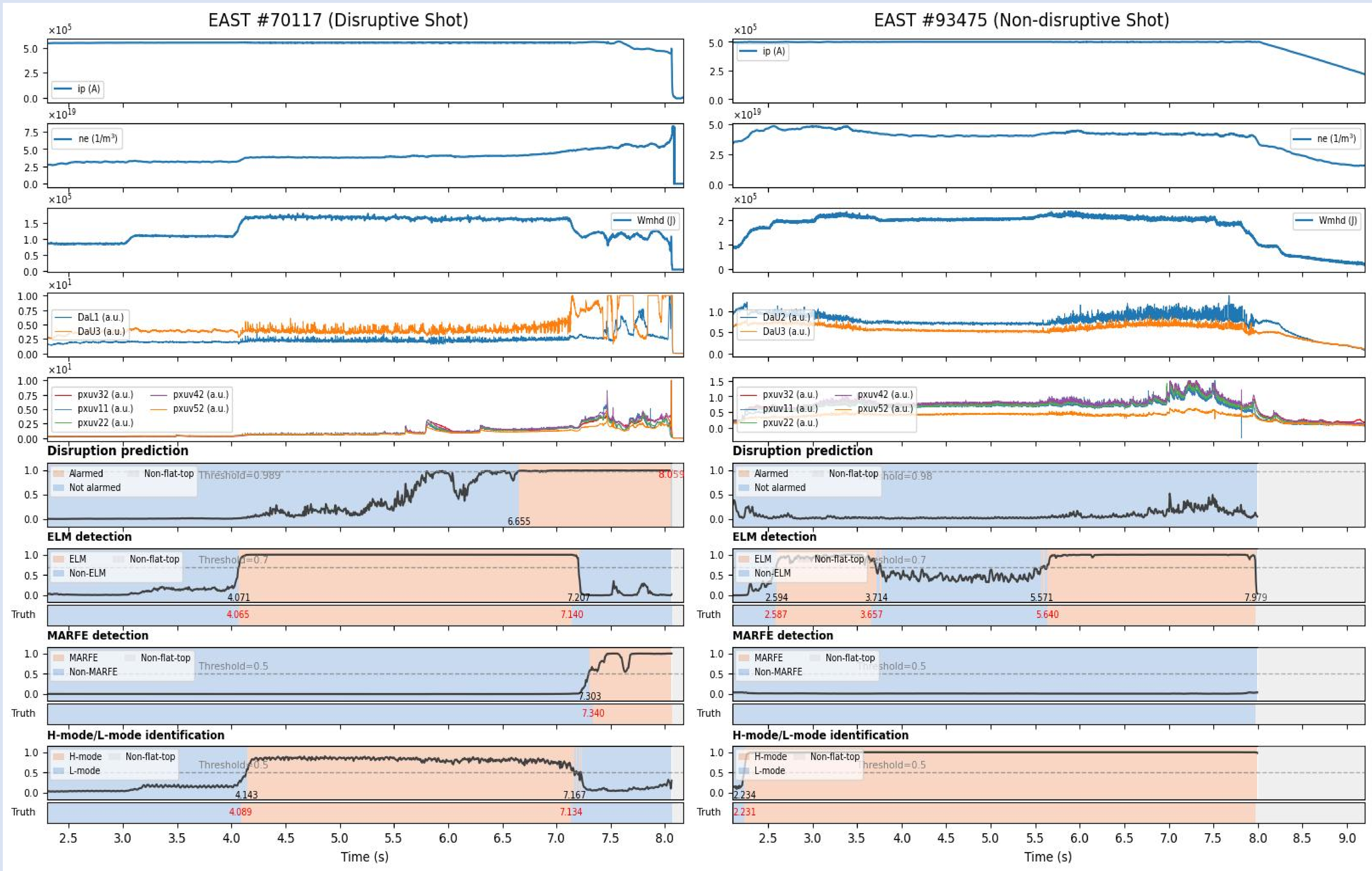

Figure 2. Model Working Examples

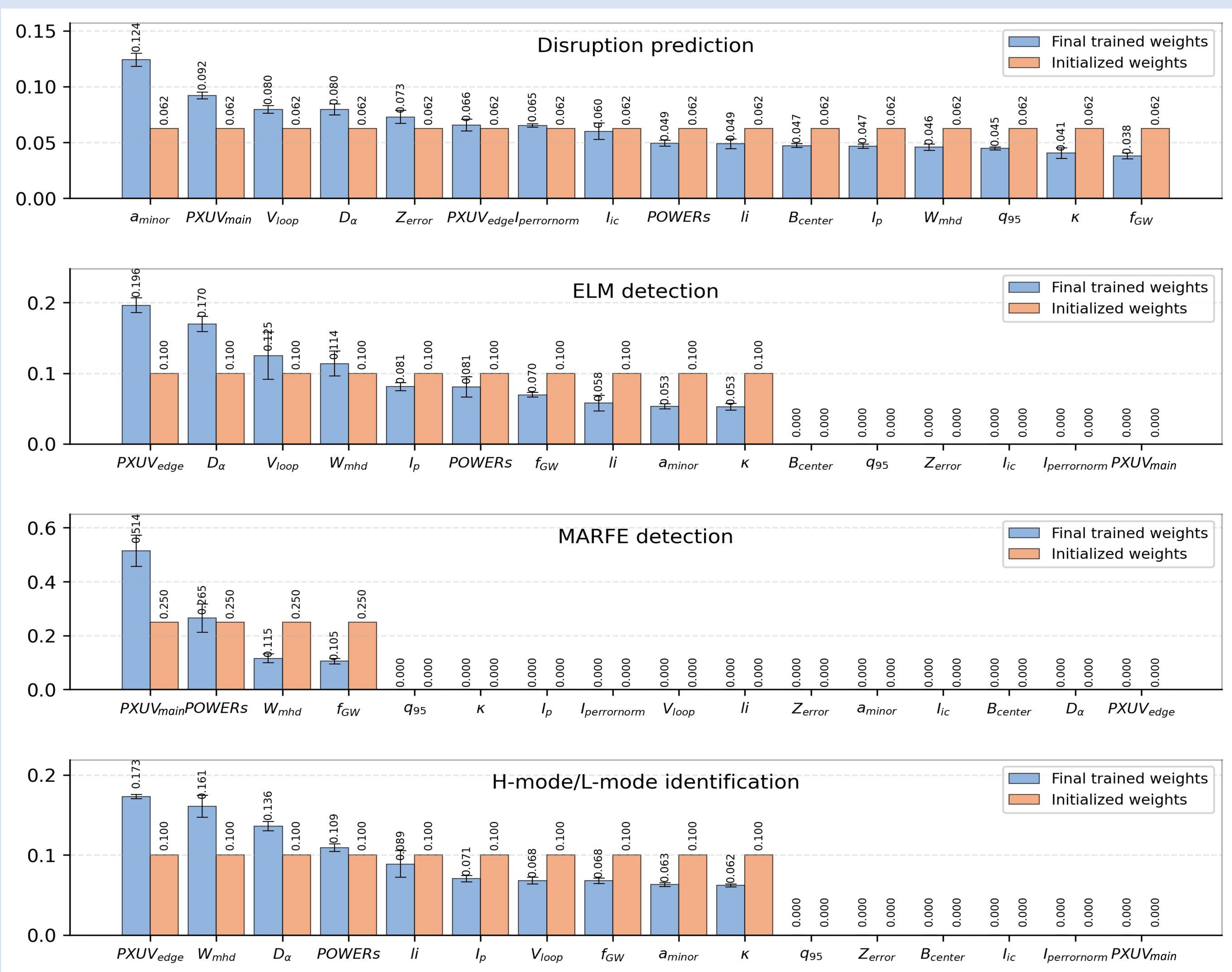

Figure 3. Gating Weights

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CONCLUSION

- We successfully addressed a critical challenge in applying multi-task learning to integrated plasma monitoring: preventing the resulting degradation in task performance. Our model significantly outperforms conventional MTL and STL baselines and achieves SOTA disruption prediction in EAST.
- The key is our model's gating modules, which employ task-specific gating modules to adaptively weigh features from specialized expert networks. This mechanism effectively manages the heterogeneous dependencies between tasks and multi-source signals.
- This work is essential for building the plasma integrated monitoring systems required for precursor-aware disruption avoidance in the future.