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

Yunhu Jia[a,b], Wenhui Hu[b,*], Bihao Guo[b], Qingquan Yang[b], Yao Huang[b], Yuehang Wang[b], Kai Wu[b], Zhengping Luo[b], Ruirui Zhang[b], Qiping Yuan[b], Bingjia Xiao[c,b,a*]

[*] *e-mail address for corresponding author: huwh@ipp.ac.cn, bjxiao@ipp.ac.cn*

[a] *University of Science and Technology of China, Hefei 230026, Anhui, China*

[b] *Institute of Plasma Physics, Hefei Institutes of Physical Science, Chinese Academy of Sciences, Hefei, 230026, Anhui, China*

[c] *Institute of Energy, Hefei Comprehensive National Science Center, Hefei 230001, Anhui, China*

Disruption prediction (DP) is crucial for tokamaks' safe operation, and detecting instability phenomena as disruption precursors is key to avoiding disruptions [1-2]. Many studies used the Single-Task Learning (STL) framework to model individual phenomena separately [3-5]. Now Multi-Task Learning (MTL) framework shows great potential for performance improvement and deployment costs reduction. On the C-Mod, DIII-D and EAST databases, Zhu et al.'s MTL-based model that integrates DP with the identification of several precursors, achieving better DP performance[6].

This study proposes a new heterogeneous-feature multi-task learning (HFMTL) framework for simultaneous DP, Edge-Localized Mode (ELM) detection, Multifaceted Asymmetric Radiation From the Edge (MARFE) detection, and Tearing Mode (TM) detection. It effectively addresses the performance degradation encountered by traditional MTL when significant heterogeneity exists in the feature spaces of different tasks. As shown in Fig. 1, Our framework employs a specially designed gated mixture-of-experts neural network, enabling each task-specific branch to select highly relevant input features through learnable gating mechanisms while suppressing interference from less relevant signals. Additionally, physics-inspired prior knowledge is embedded into the design of the loss function, further enhancing the predictive performance.

The framework is exclusively trained on the non-full-metal-wall (non-FMW) data of the Experimental Advanced Superconducting Tokamak (EAST), but tested on both unseen non-FMW data and unseen full-metal-wall data (FMW). Results show that on the non-FMW test set, the HFMTL outperforms both STL and conventional MTL methods lacking feature-gating mechanisms across all tasks. On the FMW test set, HFMTL outperforms conventional MTL in all tasks, and outperforms STL in some tasks. Notably, HFMTL achieves state-of-the-art (SOTA) performance for DP tasks on the EAST (as shown in Fig. 2a - Fig. 2b) with higher AUC and earlier warnings than prior literature, while showing promising ELM and MARFE detection capabilities (as shown in Fig. 2c -Fig. 2d).

This study supports future targeted disruption avoidance strategies, provides new insights for comprehensive plasma state monitoring, and offers a reference for addressing other heterogeneous feature multi-task learning challenges.

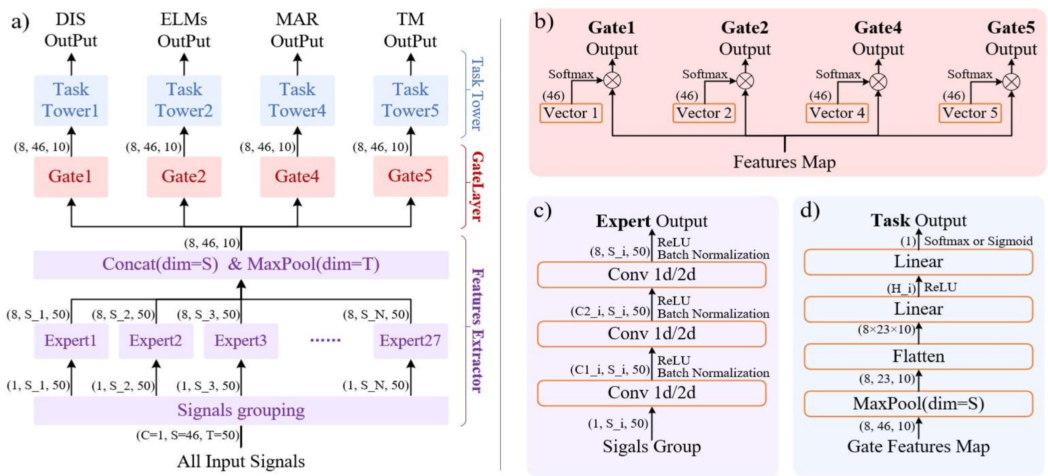
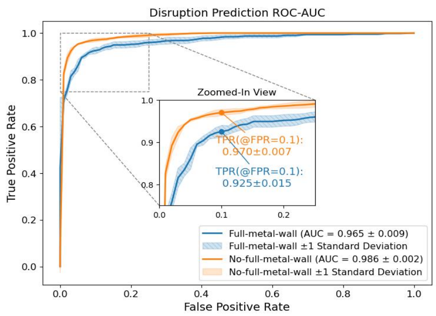
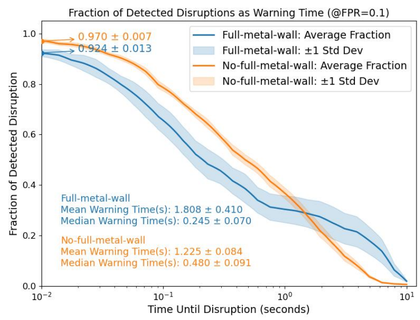


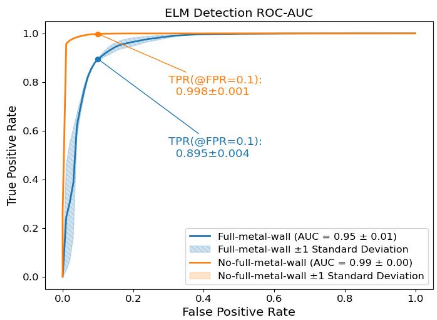
Figure 1. Architecture of gated mixture-of-experts neural network.



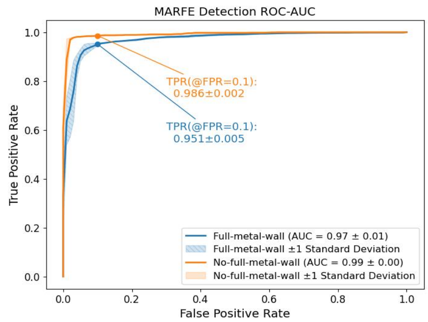
(a) Disruption Prediction ROC-AUC



(b) Fraction of Disruption Prediction as Warning Time



(c) ELM Detection ROC-AUC



(d) MARFE Detection ROC-AUC

Figure 2. Performance of the HFMTL on DP, ELM dection and MARFE detection.

Acknowledgment: This work is supported by the National MCF Energy R&D Program of China (Grant Nos. 2022YFE03010002 and 2024YFE03020003), the Institute of Energy, Hefei Comprehensive National Science Center under Grant No. 24KZS304, the National Natural Science Foundation of China (Grant Nos.12205195, 12005264, 12075285, and 11905256), and the funding support from International Atomic Energy Agency with Research Contract Number of 26478.

Reference

[1] Allen H Boozer. Theory of tokamak disruptions. Physics of plasmas, 19(5), 2012.

[2] PC De Vries, MF Johnson, B Alper, P Buratti, TC Hender, HR Koslowski, V Riccardo, JET-EFDA Contributors, et al. Survey of disruption causes at jet. Nuclear fusion, 51(5):053018,2011.

[3] David Orozco, Brian Sammuli, Jayson Barr, William Wehner, and David Humphreys. Neural network-based confinement mode prediction for real-time disruption avoidance. IEEE Transactions on Plasma Science, 50(11):4157–4164, 2022.

[4] Julian Kates-Harbeck, Alexey Svyatkovskiy, and William Tang. Predicting disruptive instabilities in controlled fusion plasmas through deep learning. Nature, 568(7753):526–531, 2019.

[5] Jaemin Seo, SangKyeun Kim, Azarakhsh Jalalvand, Rory Conlin, Andrew Rothstein, Joseph Abbate, Keith Erickson, Josiah Wai, Ricardo Shousha, and Egemen Kolemen. Avoiding fusion plasma tearing instability with deep reinforcement learning. Nature, 626(8000):746–751, 2024.

[6] JX Zhu, C Rea, RS Granetz, ES Marmar, R Sweeney, K Montes, and RA Tinguely. Integrated deep learning framework for unstable event identification and disruption prediction of tokamak plasmas. Nuclear Fusion, 63(4):046009, 2023.