Multi-Task Network-Based Confinement Mode Identification, Instability Detection and Disruption Prediction in EAST Tokamak Plasma

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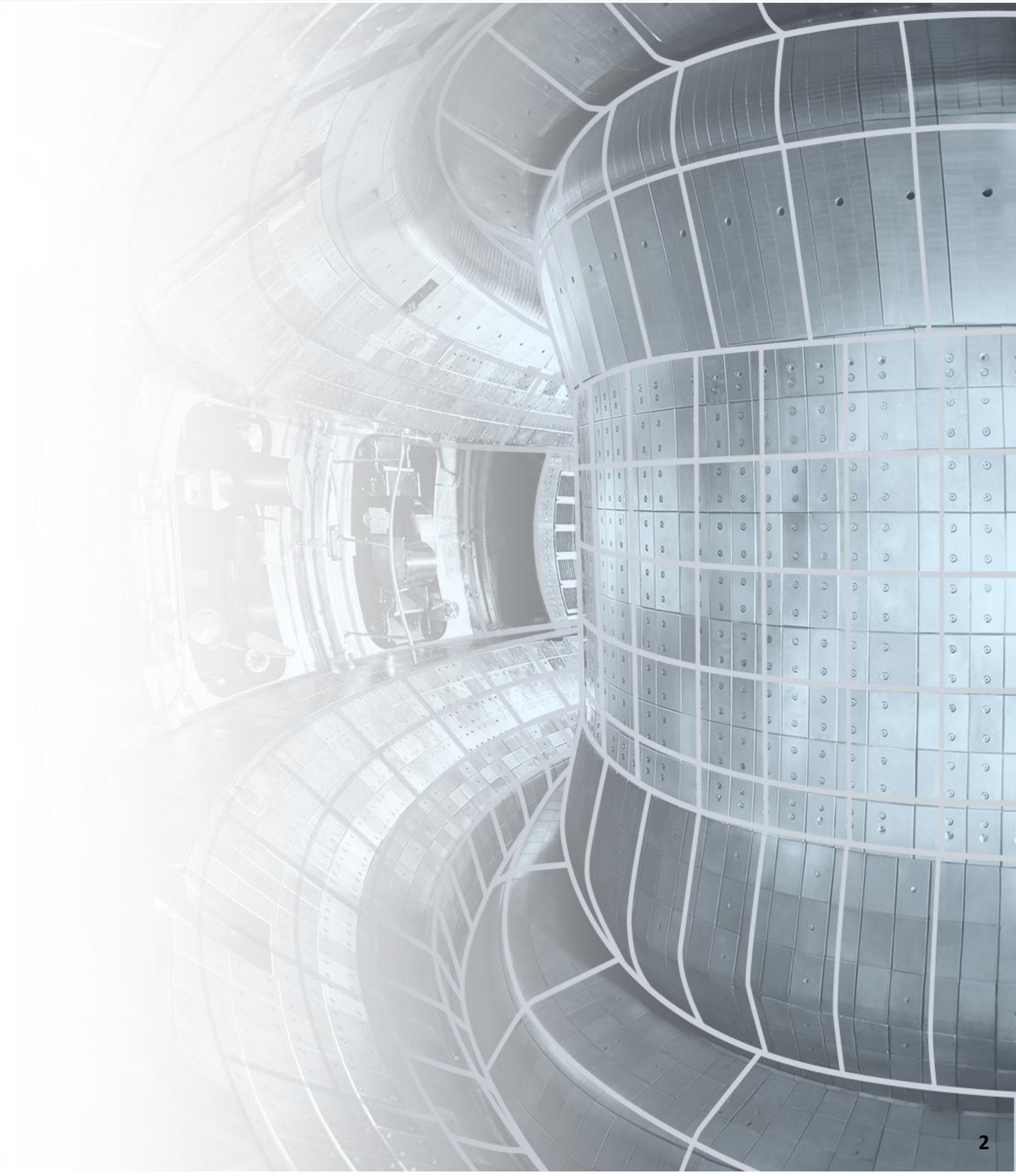
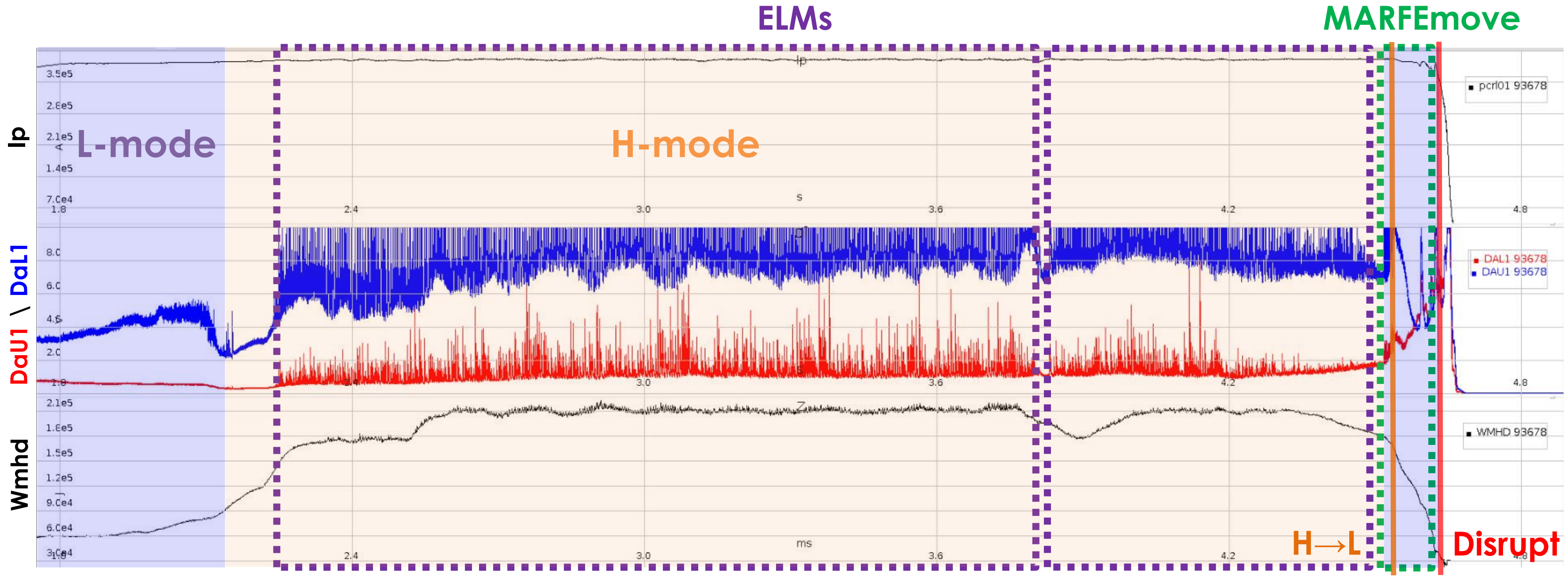


Background

- Plasma disruptions can seriously damage tokamaks, so predicting them is crucial for mitigation and avoidance.[1].
- Disruptions are usually preceded by a series of events, such as the increase of plasma instabilities and unexpected transitions in confinement modes. It is also essential to identify instabilities and confinement modes[2-4].



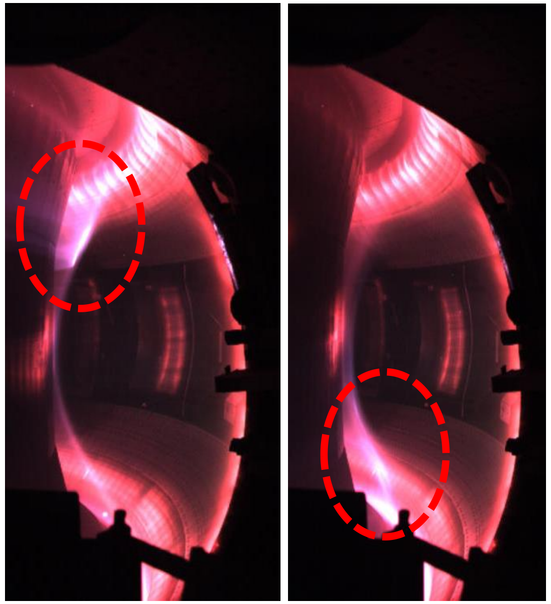


Figure 1. (Left) Event Chain of a Disruption Ending Shot (EAST #93678); (Right) MARFE Movement Observed in Camera

[1] de Vries, et al.(2016). Requirements for Triggering the ITER Disruption Mitigation System. Fusion Science and Technology, 69(2), 471–484.
[2] Diamond, Patrick H., et al. "How the Birth and Death of Shear Layers Determine Confinement Evolution: From the L → H Transition to the Density Limit." Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, vol. 381, no. 2242, Feb. 2023, p. 20210227.
[3] Seo, Jaemin, et al. "Avoiding Fusion Plasma Tearing Instability with Deep Reinforcement Learning." Nature, vol. 626, no. 8000, Feb. 2024, pp. 746–51.
[4] Orozco, David, et al. "Neural Network-Based Confinement Mode Prediction for Real-Time Disruption Avoidance." IEEE TRANSACTIONS ON PLASMA SCIENCE, vol.50, no.11,Nov 2022,pp. 4157–64,

Related Research

- Recent works highlight the potential of machine learning methods in these tasks. (Table 1)
- Some studies combine multiple tasks into a unified model/framework **(multi-task model/framework)**, enhancing performance, interpretability, and disruption avoidance[6].
- However, **EAST lacks such multi-task models/framework**, and developing a **high-performance, easily transferable** multi-task model **with limited expert annotations** remains a significant challenge.

Table 1: Current State of Related Research

Tasks	Methods and Research Content	Device	Best Performance	References
Disruption Prediction	A review on disruption prediction with artificial intelligence techniques	-	-	J. Vega, et al. Nature Phys. 18, 741-750(2022)
	CNN+Attention+MMD: Model trained on EAST carbon wall database,then transferred to metal wall database.	EAST	AUC: 0.97/0.93	[10] Guo B H, et al. 2023 Nucl.Fusion 63 094001
Instability detection	Random Forest: Prediction of MARFE-movement	EAST	ACC 85%–90%	Hu W H, et al. Chin. Phys. B 32, 075211 (2023)
	TCNN+LSTM: Identification of MHD	EAST	ACC: 98.38%	Lingyi Kong et al 2024 PlasmaPhys.Control.Fusion 66 015016
Confinement Mode identification	MLP: identification of H/I/L mode	EAST	ACC: 96.03%	[5] K.N. Yang,et al. Nucl. Fusion 64 (2024) 016035 (11pp)
	CNN: Real-time identification of H/L mode	DIII-D	ACC: 98%	David Orozco, et al. IEEE TPS, VOL.50, NO.11, 2022
	Attention+LSTM: identification of H/L mode	TCV	κ-statistic: 0.94	F.Matos,et al. Nucl. Fusion 61 (2021) 046019 (11pp)
Multiple tasks integrated	Multi-task learning: detect various instability events and simultaneously predict disruptions.	DIII-D	AUC: 0.94	[6] Zhu J X, et al. Nucl. Fusion 63 (2023) 046009 (14pp)

Our work

- We developed a multi-task model that can handle disruption prediction, macro-instability event detection (ELMs and MARFE Movement), and confinement mode Identification (H/I/L mode or only ohmic heating) at the same time.
- In EAST carbon wall database, Our multi-task model achieved state-of-the-art (SOTA) performance in disruption prediction and ELMs detection tasks, and showed performance improvements in other tasks compared to single-task models.
- As shown in Fig.2, Our model's input includes the current time and a 100ms data window before it. The output is the result of various tasks at the current time. All signals are from the Plasma Control System (PCS) with a sampling rate of 1 kHz, making the model suitable for real-time applications.

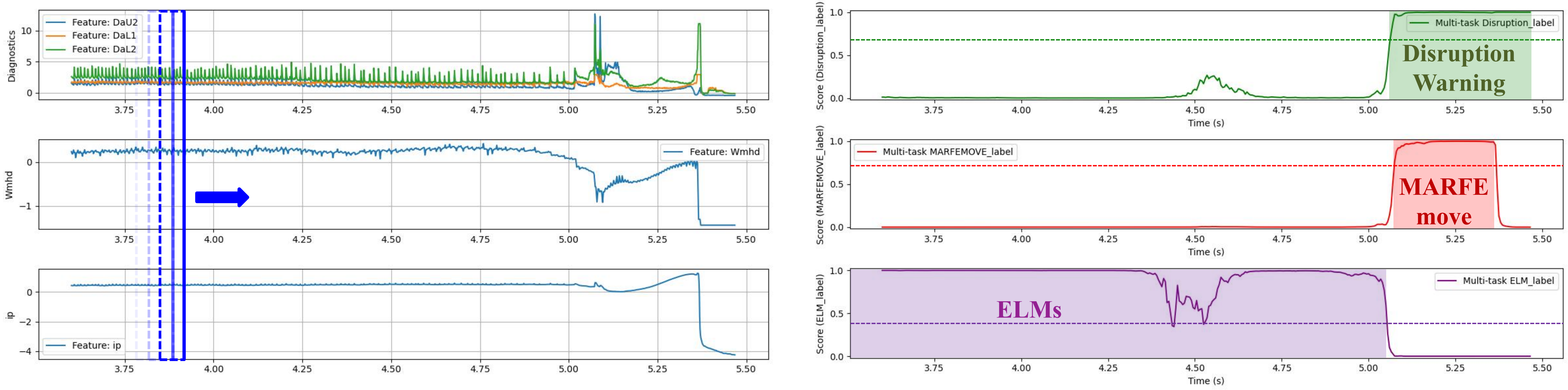


Figure 2. Examples of Partial Input and Output of the Multi-Task Model

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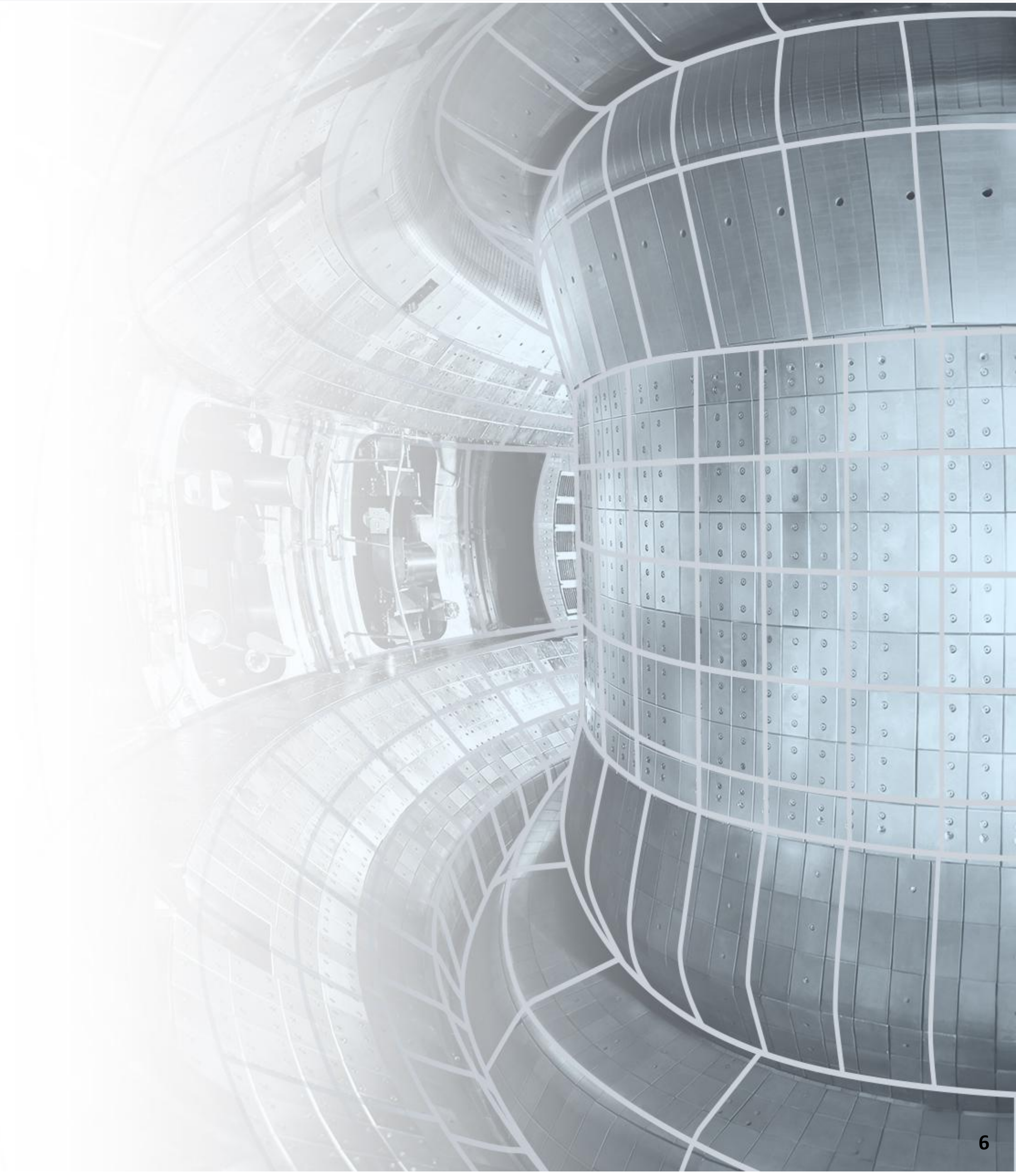

Data source

- Extensive expert annotations were conducted on 9,756 shots from the EAST database during the period from 2015 to 2019. Some of the expert annotations have already been used in previous research [5,6,8,9].
- To facilitate comparison with the recorded results on EAST [10], the disruption database shots are divided into four sets based on Bihao Guo's research (Table 3).

Table 3: Expert annotations (Expert list: Hu Wenhui, Guo Bihao, Yang Qinquan, Lin Xin, Liu Adi, Hou Jilei)

Annotation	Training Set (Time unit /s)	Validation Set (Time unit /s)	Carbon Wall Test Set (Time/s)	Metal Wall Test Set (Time/s)
Disruption_label	Shots Number:6516 Pos Time:199.3,Neg Time:31425.3	Shots Number:1399 Pos Time:43.1,Neg Time:6834.73	Shots Number:1234 Pos Time:43.7,Neg Time:5697.97	Shots Number:297 Pos Time:8.0,Neg Time:1628.52
ELM_label	Shots Number:130 Pos Time:401.94,Neg Time:517.81	Shots Number:29 Pos Time:63.08,Neg Time:136.69	Shots Number:31 Pos Time:70.01,Neg Time:154.4	Shots Number:133 Pos Time:531.5,Neg Time:682.86
MARFEmove_label	Shots Number:21 Pos Time:7.61,Neg Time:56.8,	Shots Number:5 Pos Time:4.48,Neg Time:10.9	Shots Number:6 Pos Time:3.68,Neg Time:13.86	Shots Number:49 Pos Time:24.62,Neg Time:370.8
H_Mode_label	Shots Number:84 Pos Time:422.37,Neg Time:0.0,	Shots Number:15 Pos Time:71.69,Neg Time:0.0	Shots Number:16 Pos Time:74.07,Neg Time:0.0	Shots Number:101 Pos Time:532.2,Neg Time:0.0
I_Mode_label	Shots Number:53 Pos Time:80.6,Neg Time:0.0,	Shots Number:17 Pos Time:24.44,Neg Time:0.0	Shots Number:21 Pos Time:31.94,Neg Time:0.0	Shots Number:19 Pos Time:39.74,Neg Time:0.0
L_Mode_label	Shots Number:46 Pos Time:80.4,Neg Time:0.0,	Shots Number:10 Pos Time:26.82,Neg Time:0.0	Shots Number:19 Pos Time:38.48,Neg Time:0.0	Shots Number:10 Pos Time:101.1,Neg Time:0.45
OHM_Mode_label	Shots Number:26 Pos Time:131.06,Neg Time:0.0,	Shots Number:10 Pos Time:43.57,Neg Time:0.0	Shots Number:10 Pos Time:52.77,Neg Time:0.0	Shots Number:21 Pos Time:107.72,Neg Time:0.0

Input Signal

- Selection Principles of input signal: a) based on prior physical knowledge and previous papers[3-9]; b) capability in PCS; c) minimal signal quantity to avoid the "curse of dimensionality".
- Utilizing Short-Time Fourier Transform (STFT) on Da signals to extract time-frequency information for feature enhancement.

Table 3: Signal Selection

Symbol	Signal description	Symbol	Signal description
p_RAD	Radiated power	rad_input_frac	$\frac{Radiated\ power}{Input\ power}$
DaL1	Deuterium Balmer-a line emission spectrum (lower first channel)	DaU2	Deuterium Balmer-a line emission spectrum (upper second channel)
ne	Electron density	Z_cur_lmsz	Linearly estimated vertical displacement
ip	Plasma current	pxuv32	Bolometric radiation measurement
Wmhd	Plasma stored energy	p_LH	Lower hybrid heating power
v_loop	Loop voltage	kappa	Elongation ratio
ip_error_normalized	$\frac{Plasma\ current - Programed\ plasma}{current\ Programed\ plasma}$	Greenwald_fraction	$\frac{Electron\ density}{Greenwald\ density}$
q95	Safety factor at the 95% flux surface	ne_error	density – current programed plasma density
STFT_DaU2_50-100Hz	STFT of DaU2 in the 50-100 Hz range	STFT_DaL1_50-100Hz	STFT of DaU2 in the 50-100 Hz range
STFT_DaU2_100-150Hz	STFT of DaU2 in the 100-150 Hz range	STFT_DaL1_100-150Hz	STFT of DaL1 in the 100-150 Hz range
STFT_DaU2_150-200Hz	STFT of DaU2 in the 150-200 Hz range	STFT_DaL1_150-200Hz	STFT of DaL1 in the 150-200 Hz range

[7] Kim, S.K., Shousha, R., Yang, S.M. et al. Highest fusion performance without harmful edge energy bursts in tokamak. Nat Commun 15, 3990 (2024).

[8] Hu, Wenhui, et al. "Prediction of Multifaceted Asymmetric Radiation from the Edge Movement in Density-Limit Disruptive Plasmas on Experimental Advanced Superconducting Tokamak Using Random Forest." Chinese Physics B, vol. 32, no. 7, July 2023, p. 075211. Institute of Physics,

[9] W.H. Hu, et al. "Real-Time Prediction of High-Density EAST Disruptions Using Random Forest." Nuclear Fusion, vol. 61, no. 6, June 2021, p. 066034.

Our Model Structure

- The model has a feature extractor and several task classifiers. The feature extractor is a multi-scale convolutional network[6], and the task classifiers are linear fully connected neural networks.
- Model input: current time and preceding 100ms window (22*100 data points).To enhance performance, attempt to construct cascade relationships between task classifiers.
- All hyperparameters for each model are obtained using a genetic algorithm on the validation set.

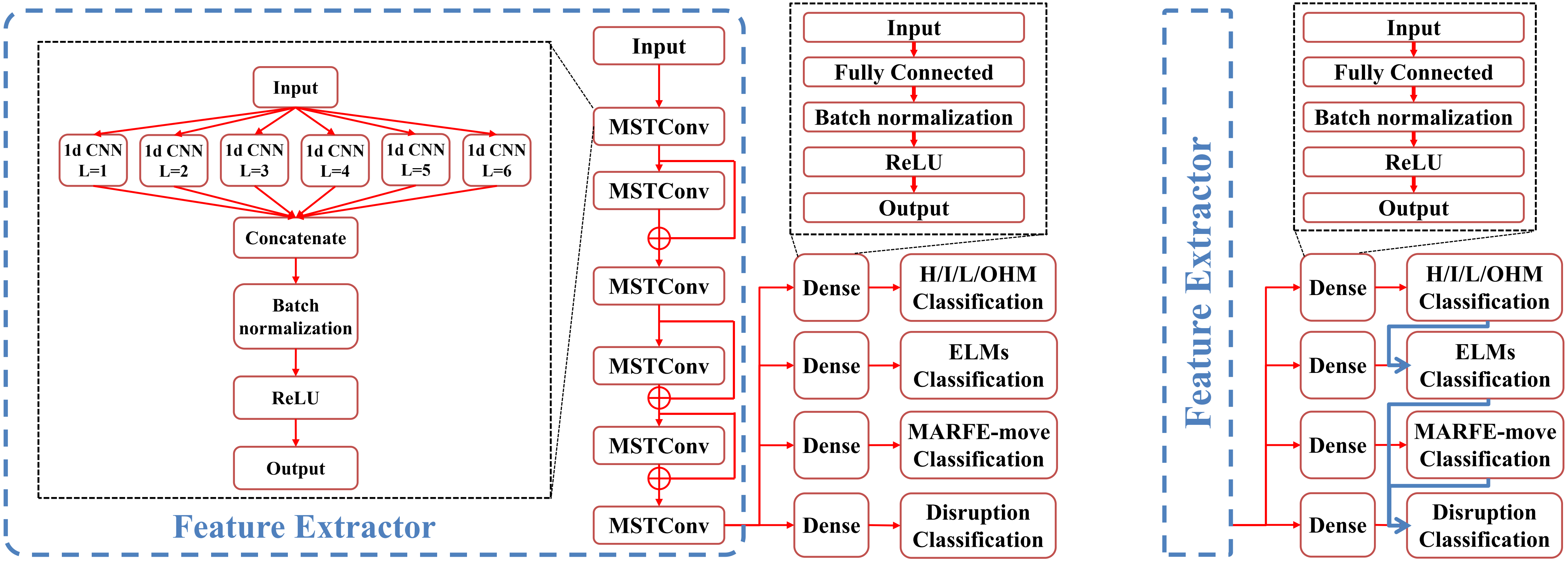

Figure 3. (Left) Parallel configuration of task classifiers; (Right) Cascade configuration of task classifiers.

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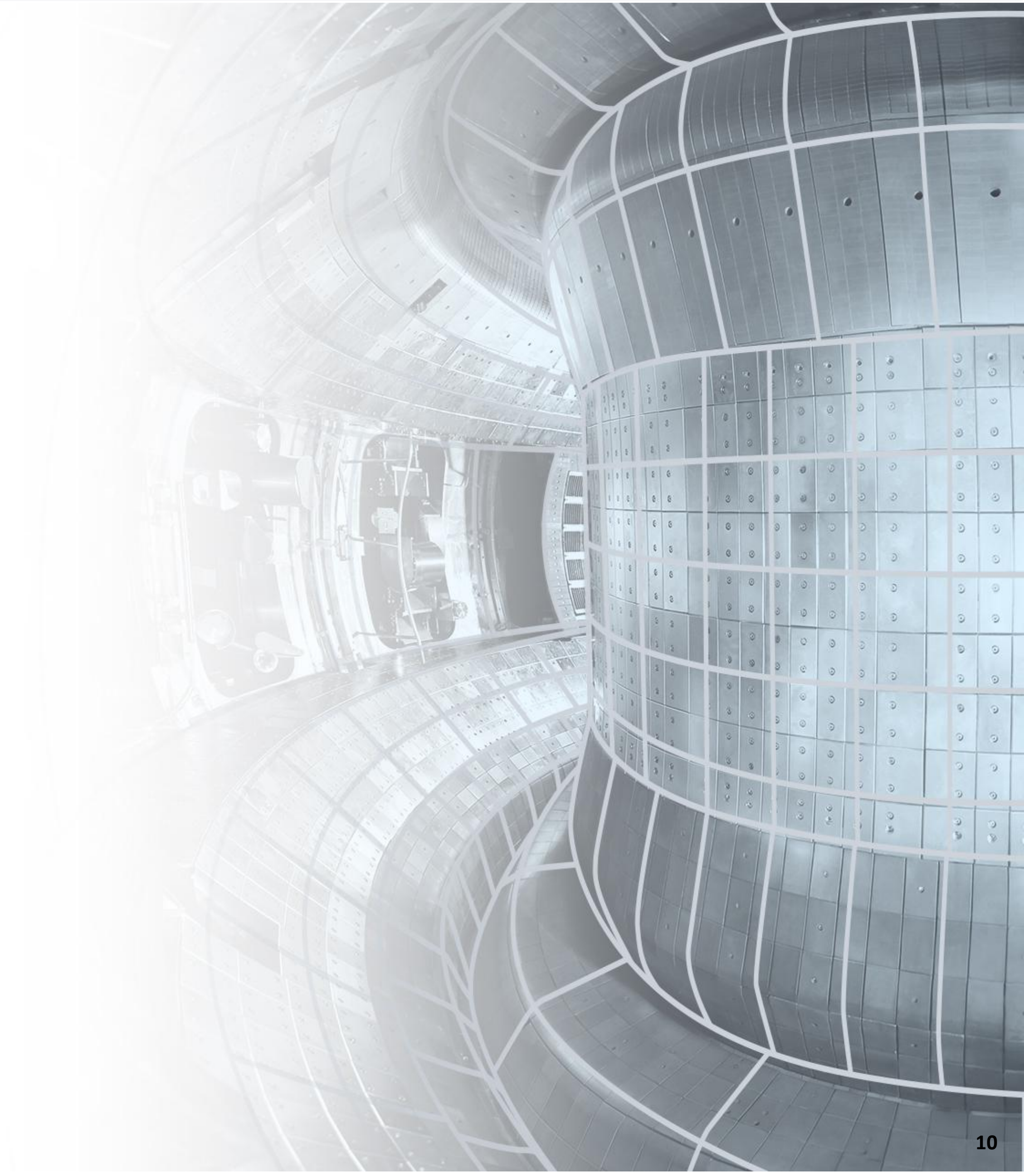

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Best disruption prediction: multi-task cascade model

- For the disruption prediction task, the multi-task model significantly outperforms the single-task model in terms of prediction accuracy and provides earlier warnings.
- Additionally, the performance of the multi-task cascade model is slightly superior to that of the multi-task parallel model, representing the highest performance on EAST carbon wall database.

This ROC curve shows the True Positive Rate vs. False Positive Rate for different thresholds. The red line indicates random guessing (AUC = 0.5). Higher AUC means better performance.

The x-axis shows the lead time before disruption (warning time), and the y-axis shows the fraction of disruptions detected by that time.

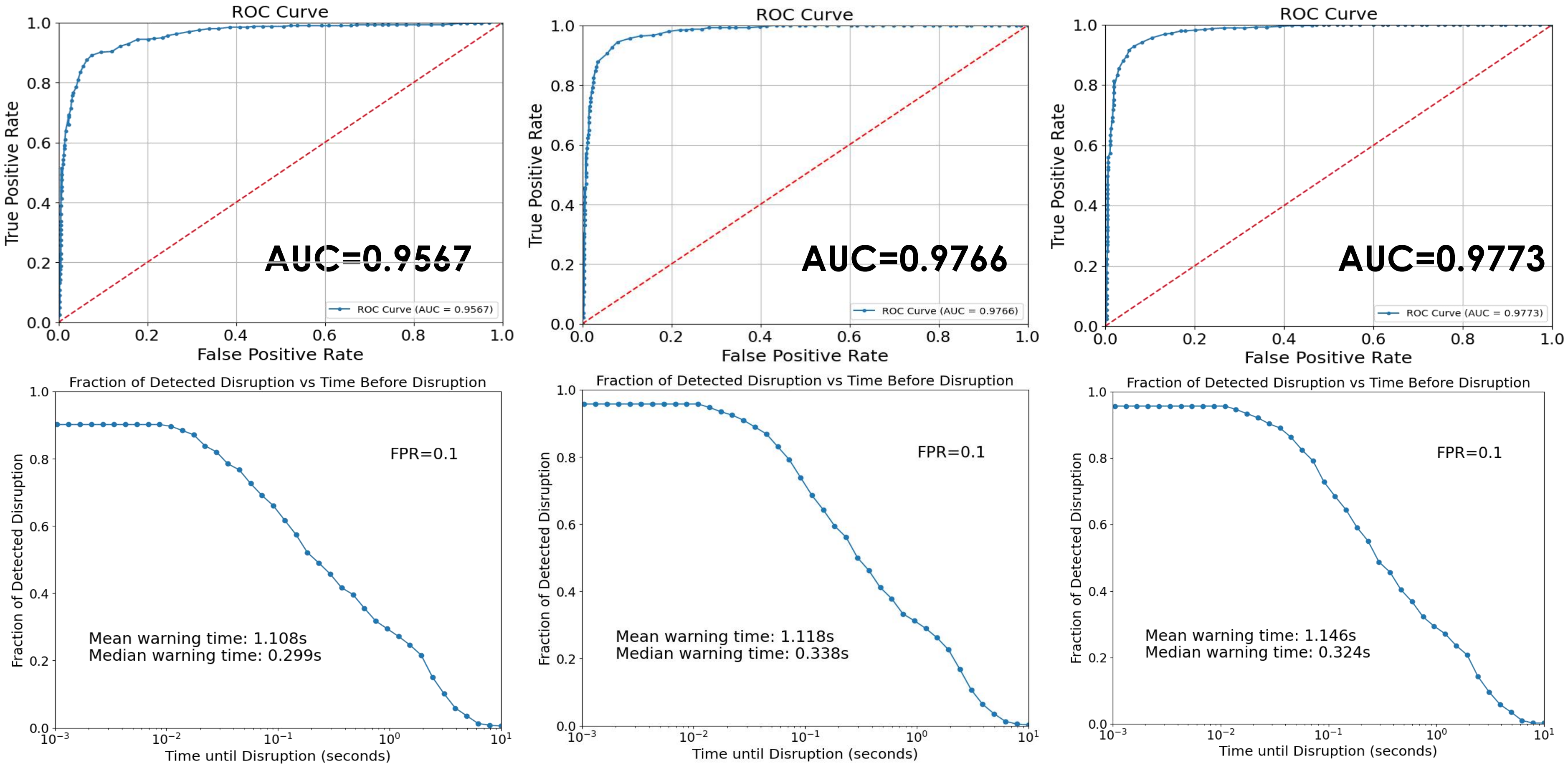


Figure 4: (Left) Single-task model; (Middle) Multi-task parallel model; (Right) Multi-task cascade model.

Best instability detection: multi-task cascade model

- The performance of instability detection tasks in cascade networks surpasses that of parallel networks, which in turn exceeds the performance of single-task models.
- The ELM detection AUC is 0.991, the best performance so far on EAST carbon wall database.

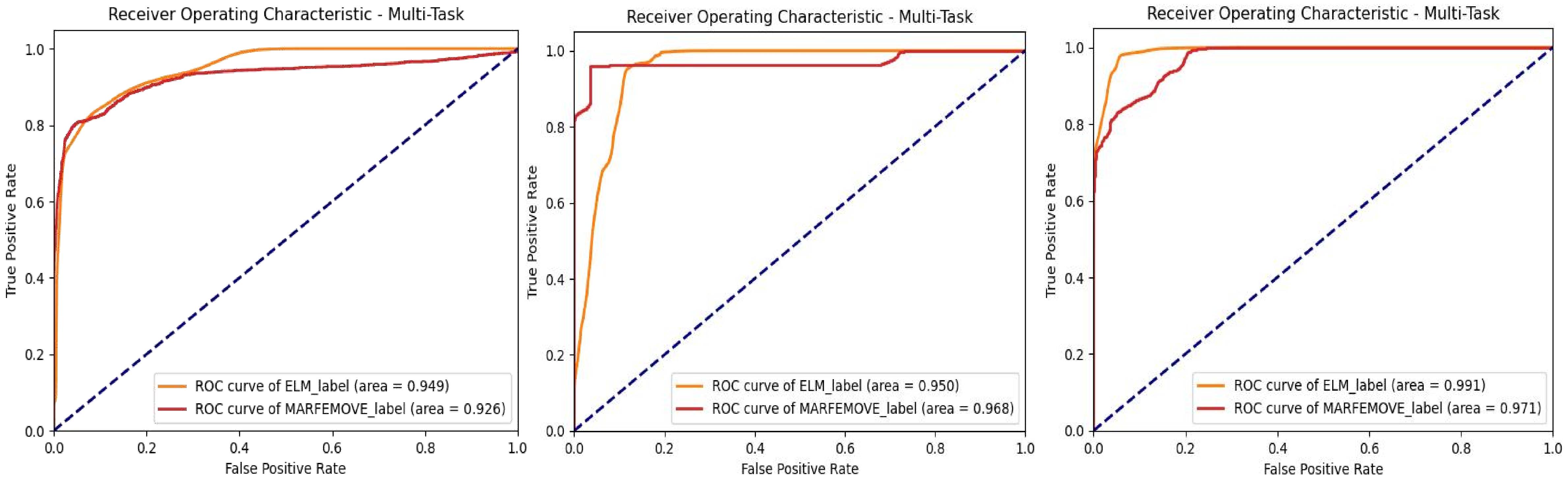
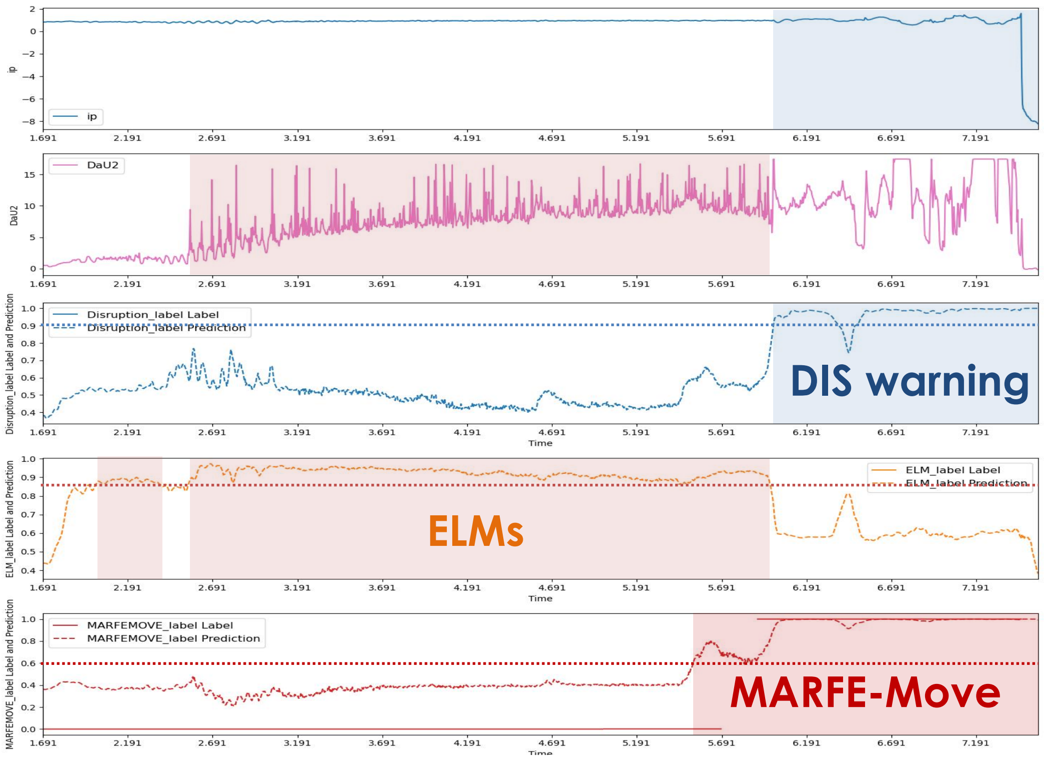
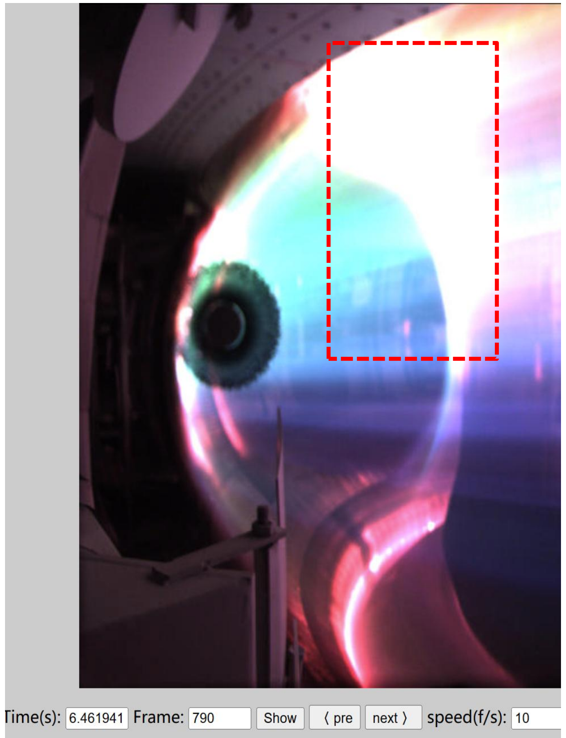


Figure 5: (Left) Single-task model; (Middle) Multi-task parallel model; (Right) Multi-task cascade model.

Correlation between instability detection and disruption prediction

- Through multi-task joint learning, it was observed that instability detection tasks impact disruption prediction, enhancing both interpretability and performance of the predictions.
- The detection score of ELMs is negatively correlated with disruption risk, while the detection score of MARFE movement is positively correlated with disruption risk. This implies the presence of ELMs decrease disruption risk, while MARFE movement increases it, matching experimental experience.





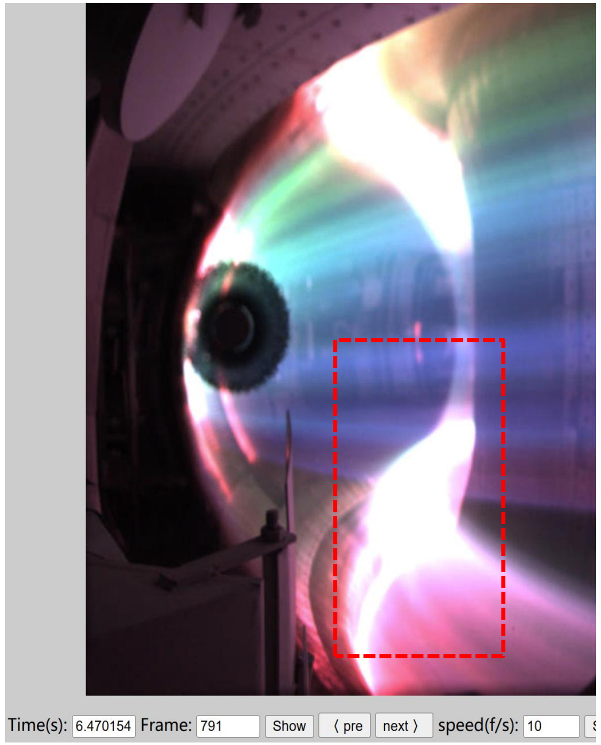
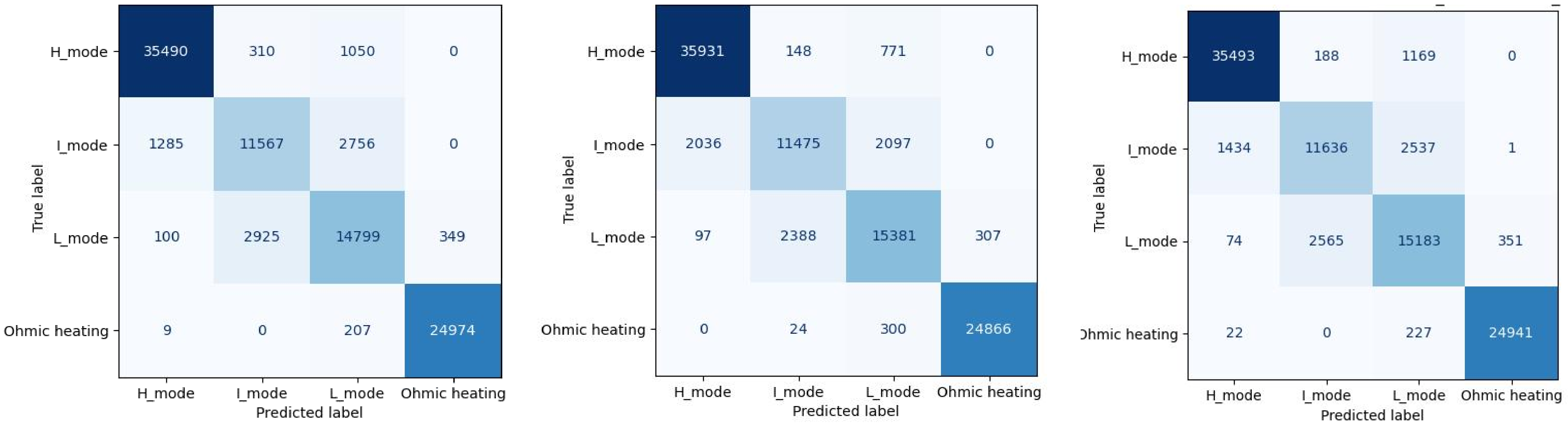


Figure 6. Instability detection and disruption prediction impact each other (EAST Test Shot: 70611)

Best Confinement Mode Identification: multi-task parallel model

- For confinement mode identification, the model outputs the class with the highest score directly. Therefore, model performance can be directly measured by the ACC from the confusion matrix.
- The optimal model is the parallel model, achieving an ACC 91.48%, which is below the performance reported in the literature[5]. However, ours does differs from theirs not not require high-frequency signals to detect WCM, making it better suited for the real-time operational characteristics of PCS.



ACC 90.61% **ACC 91.48%** **ACC 91.06%**

Figure 7: (Left) Single-task model; (Middle) Multi-task parallel model; (Right) Multi-task cascade model.

Confinement Mode Transition Identification

- The model can dynamically identify H-mode, L-mode, I-mode, or only ohmic heating. It can also indirectly identify the transitions between different confinement modes.

- However, the accuracy of transition identification (Specific time of transition) needs improvement.

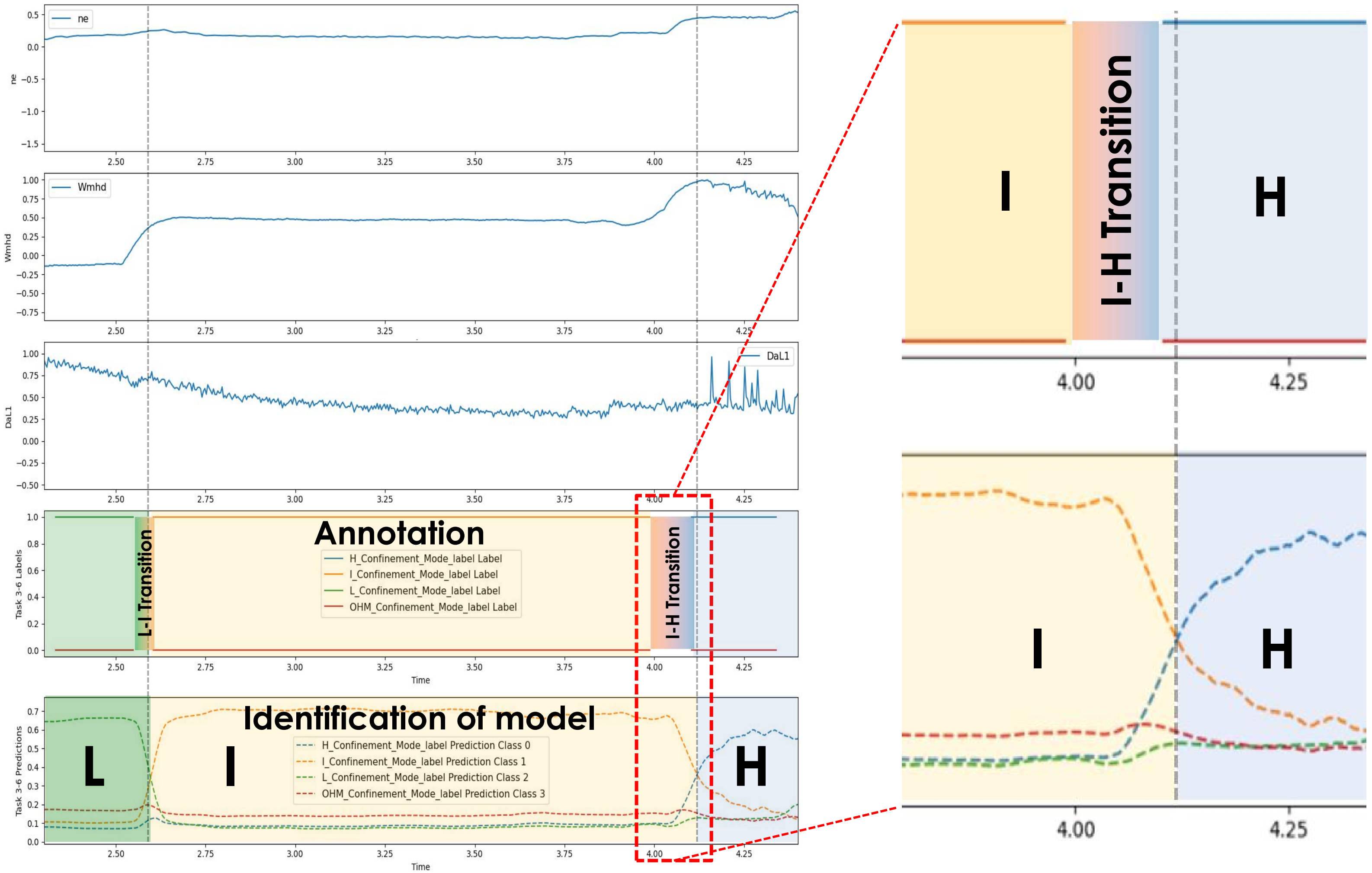


Figure 8. Confinement mode identification (EAST Test Shot: 77572)

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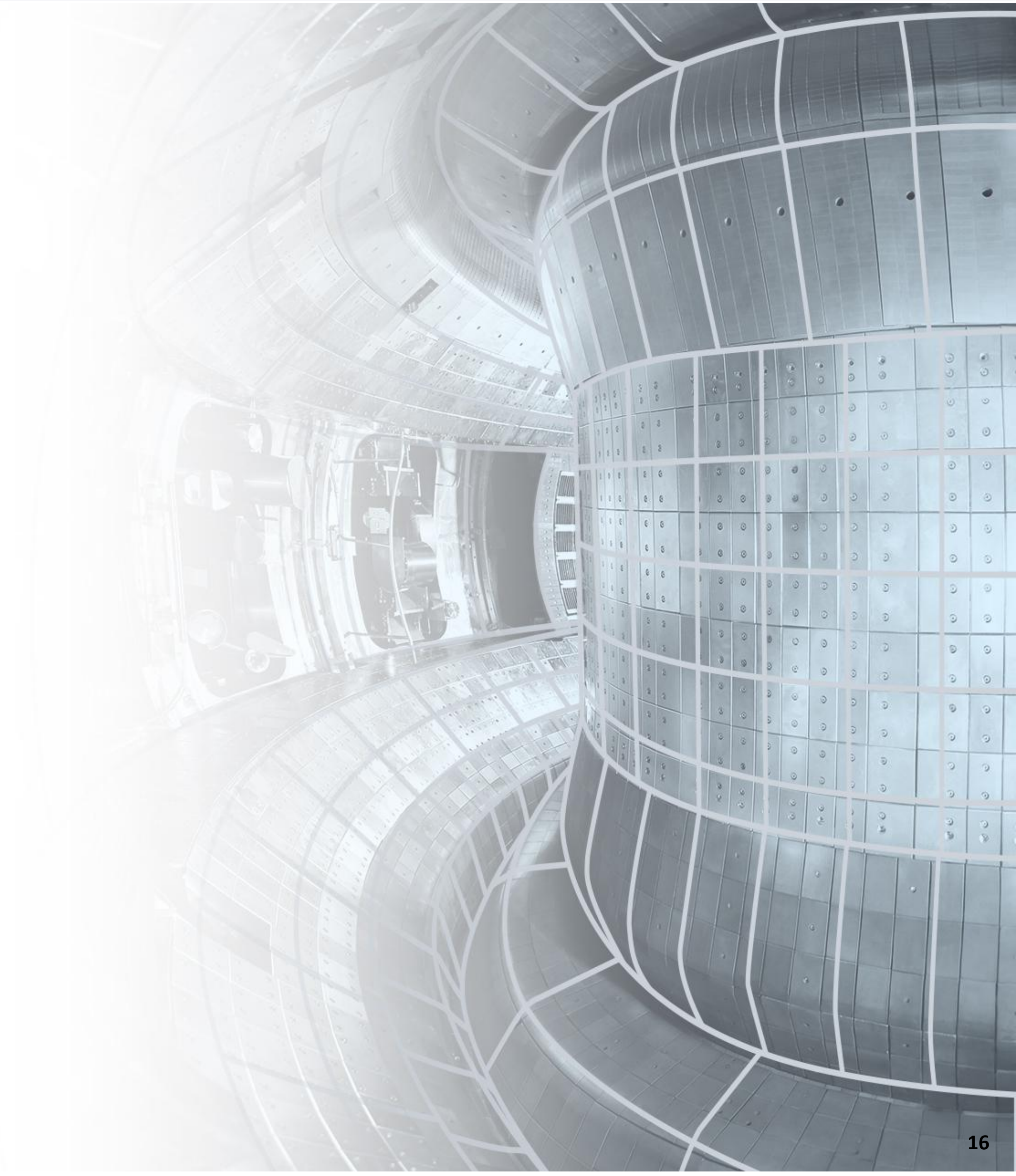


Enhancing Transition and Cross-Wall Performance

- To enhance the performance in identifying the specific time of transition, a specialized transition identification task is added based on the confinement mode recognition.
- To address the issue of performance degradation across walls[10], a domain adversarial task is added.

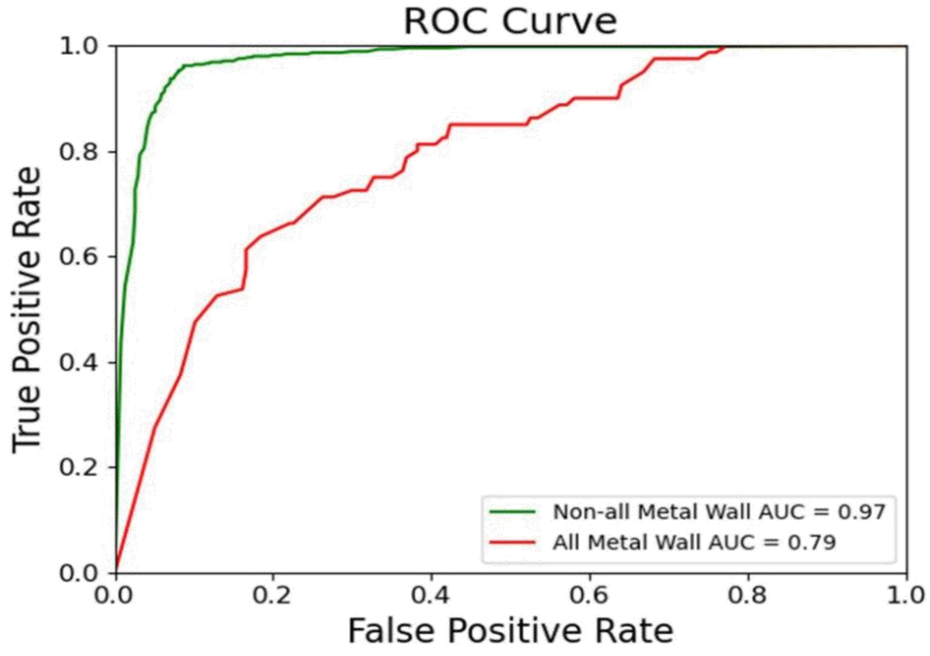


Figure 9. performance declines when working across walls[10]

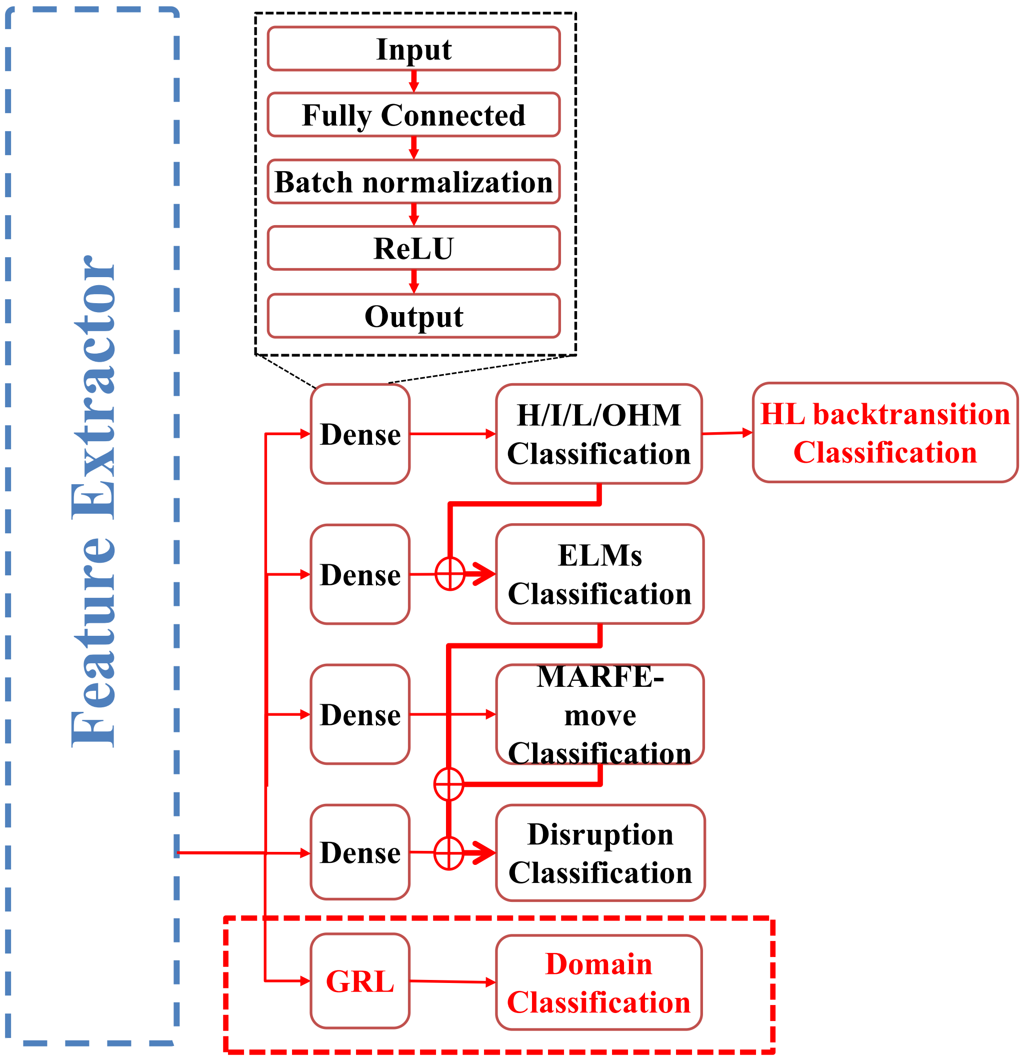
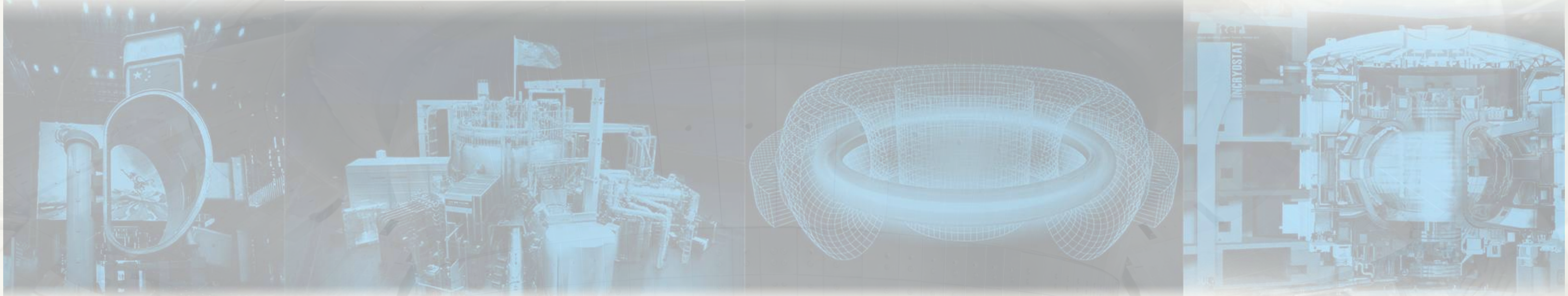


Figure 10. Future model structure

[10] Guo, B. H., et al. Nuclear Fusion, vol. 63, no. 9, July 2023, p. 094001. Institute of Physics,



Thank you !