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Adaptive Anomaly Detection Disruption Prediction Starting from First Discharge

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Plasma disruption presents a significant challenge in tokamak fusion, especially in large-size devices like ITER, where it can cause severe damage and economic losses. Current disruption predictors mainly rely on data-driven methods, requiring extensive discharge data for training. However, future tokamaks require disruption prediction from the first shot, posing challenges of data scarcity and difficulty in training and parameter selection during the initial operation period. In this period disruption prediction aims to support safe operational exploration and accumulate necessary data to develop advanced prediction models. Thus, predictors must adapt to evolving plasma environments during this exploration phase. To address these challenges, this study proposes a cross-tokamak adaptive deployment method using the Enhanced Convolutional Autoencoder Anomaly Detection (E-CAAD) predictor. This method enables disruption prediction from the first discharge of new devices, addressing the challenges of cross-tokamak deployment of data-driven disruption predictors. The E-CAAD model, trained on non-disruption samples and using disruption precursor samples when available, suits unpredictable data environments on new device. During inference, the E-CAAD model assesses input samples by compressing and then reconstructing them, using the reconstruction error (RE) to measure the similarity between the input and reconstructed samples. The model trained by ample data return smaller REs for normal samples and larger REs for disruption precursor samples, allowing for the setting of an RE threshold to achieve disruption prediction. Experimental results reveal significant differences in the REs returned by the E-CAAD model trained on the existing device for disruption precursor samples and non-disruption samples on the new device. Therefore, the model from the existing device can achieve disruption prediction for the first shot on the new device by adjusting the warning threshold. Building upon this, adaptive learning from scratch strategy and warning threshold adaptive adjustment strategy are proposed to achieve model cross-device transfer. The adaptive learning from scratch strategy enables the predictor to fully use scarce data during the initial operation of the new device while rapidly adapting to changes in operating environment. The warning threshold adaptive adjustment strategy addresses the challenge of selecting warning thresholds on new devices where validation and test datasets are lacking, ensuring that the warning thresholds adapt to changes in the operating environment. Finally, experiments transferring the model from J-TEXT to EAST exhibit comparable performance to EAST models trained with ample data, achieving a TPR of 85.88% and a FPR of 6.15%, with a 20ms reserved MGI system reaction time.

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