J-TEXT's Efforts on Disruption Prediction of Future Rectors

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Introduction

Background

Accurate disruption prediction is one of the keys for tokamaks to be commercially viable reactors. But these are some chanlleges for future tokamak disruption prediction.

- ☐ During the initial operation of the new device, the data is scarce, so it is difficult for model training and hyperparameter selection.
- ☐ Due to differences in structure, operating parameters, and other factors, the data driven models are difficult to transfer between tokamaks.
- ☐ Machine learning models struggle with cross-machine general-ization and scenario adaptation.

Work

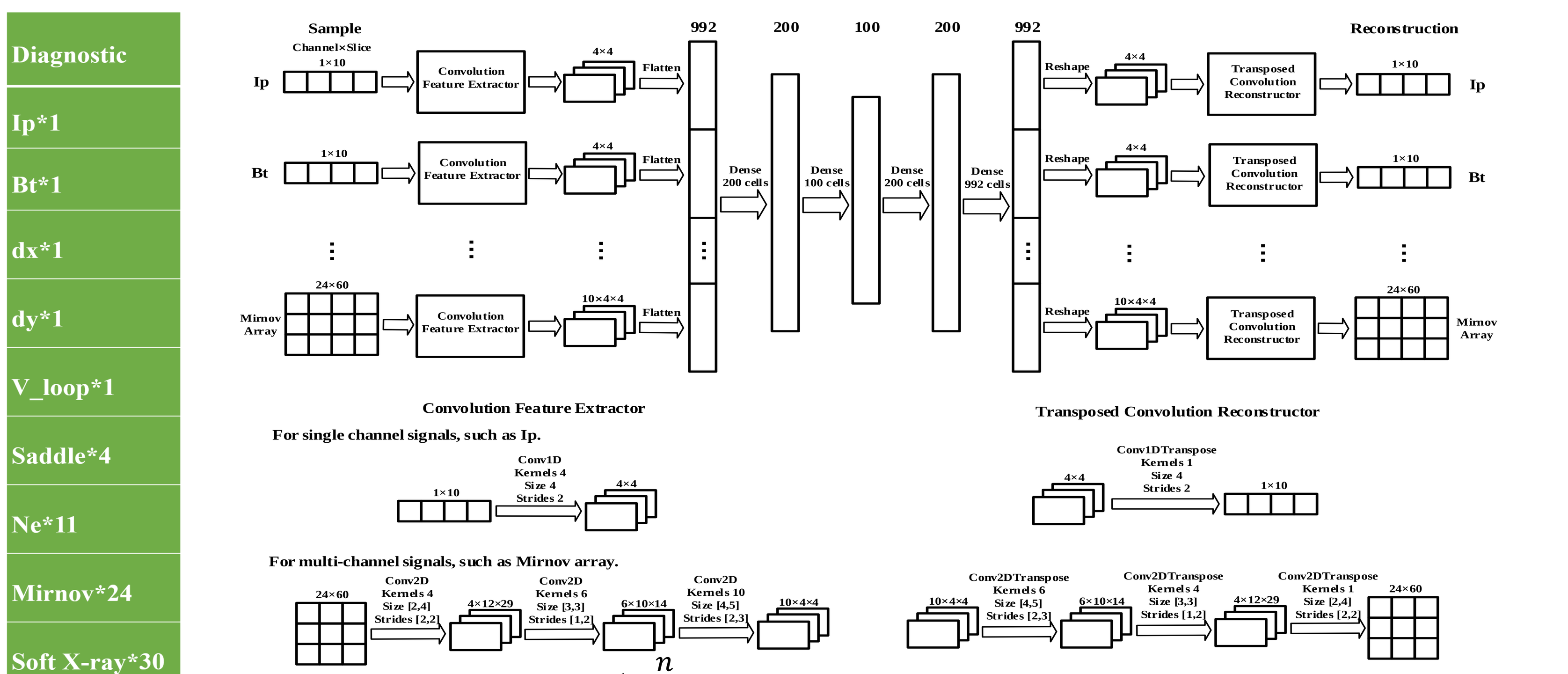
We propose a phased strategy for different operational phases:

- ➢ Anomaly detection from the first shot.
- ➢ Physics-guided transfer learning with limited data.
- ➢ Disruption Budget Consumption (DBC) for risk-aware evaluation

Anomaly Detection & Cross-Tokamak Transfer

☐ **Developed E-CAAD anomaly detection model**

- ➢ Trained on non-disruptive samples, uses disruptive precursors when available.



$$Loss = \frac{1}{n}\sum_{i=1}^{n}\left[y \cdot RCE_i^{y} + (1-y)\cdot \alpha \cdot RCE_i^{y-1}\right]$$

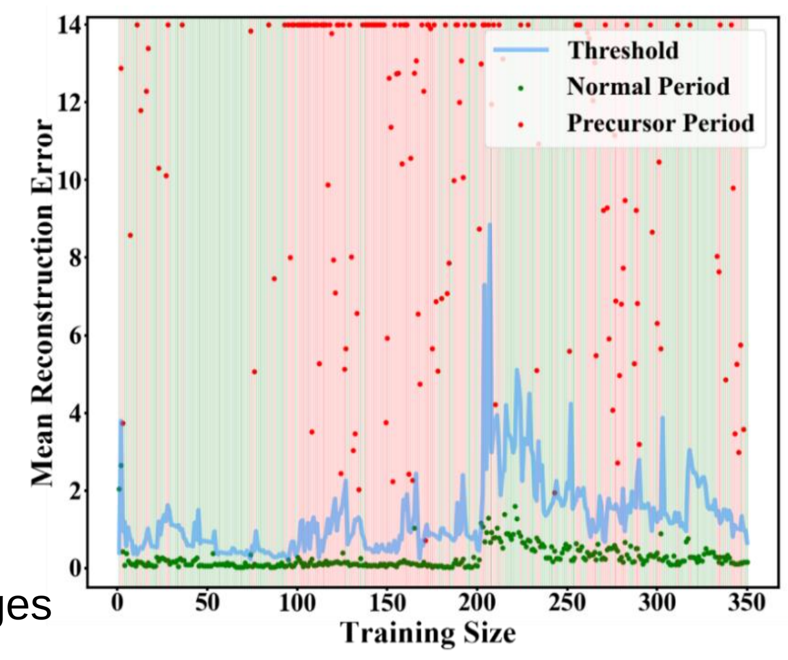
☐ **Trained on J-TEXT, deployed on EAST from first discharge.**

☐ **Strategies:**

- ➢ Existing-machine data assistance.
- ➢ Adaptive learning from scratch.
- ➢ Adaptive alarm threshold adjustment.

☐ **Result**

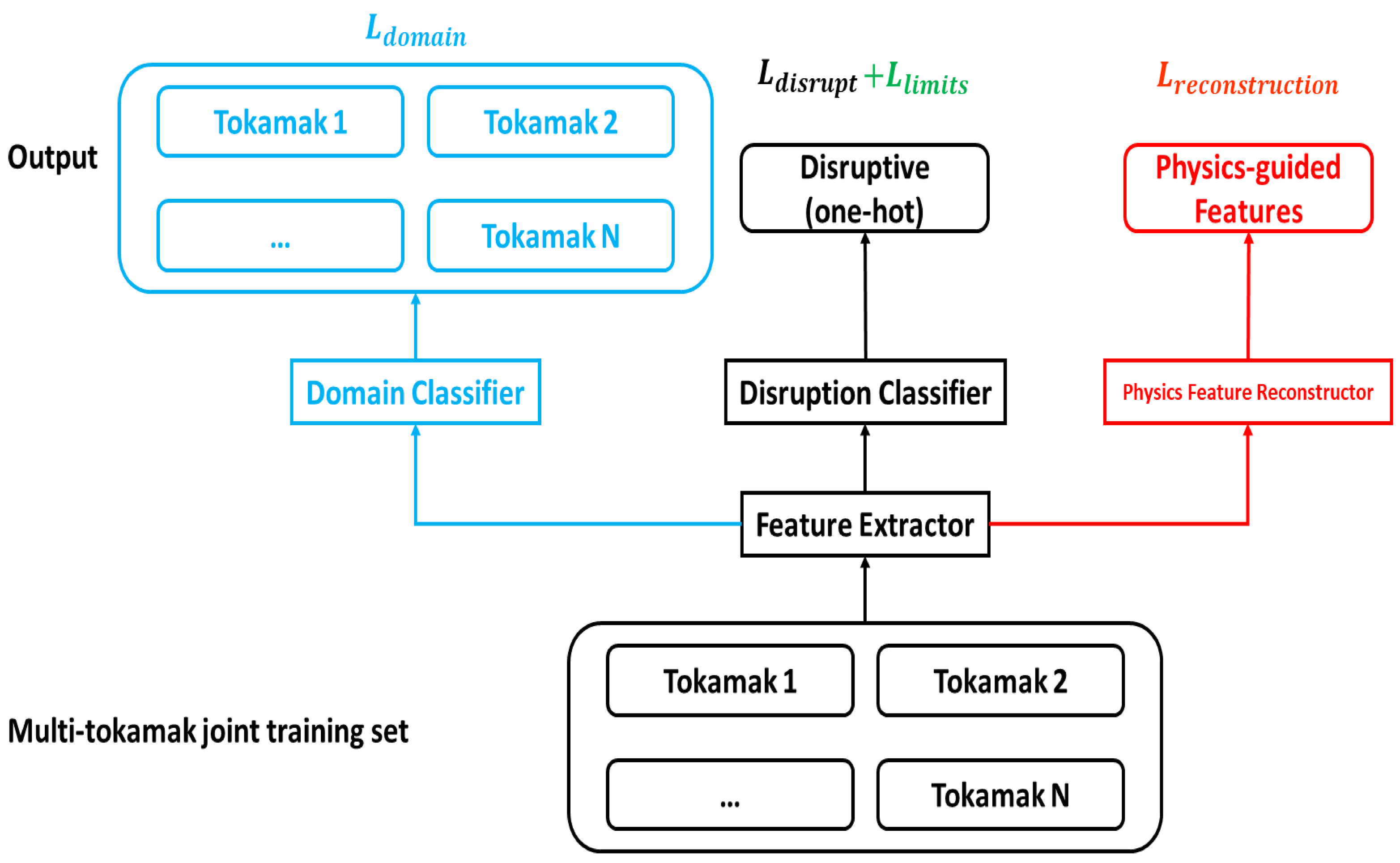
- ➢ Disruption prediction from the first discharge.
- ➢ Model automatically adapts to dynamic changes in operation scenarios



Physics-Guided Transfer Learning

☐ **Physics-guided Domain Adaptation Network (PhyDANet)**

- ➢ Combines physics constraints (e.g., density, q-limits) with ML.
- ➢ Uses domain adaptation (DANN, MMD) + reconstruction.



☐ **Result**

	Data	+ Physical Loss	+Reconstruction	No physics guidance
Only EAST	2 shots	0.8357	0.8039	0.7992
	20 shots	0.8902	0.9053	0.8756
J-TEXT+EAST Domain Generalization	J-TEXT 1021 shots EAST 2 shots	0.8026	0.7762	0.8094
	J-TEXT 1021 shots EAST 20 shots	0.9449	0.9475	0.9212

- ➢ 2 EAST shots: Physical loss boosts performance.
- ➢ 20 EAST shots: Domain adaptation + reconstruction → TPR > 94%.

Disruption Budget Consumption (DBC) Framework

☐ **Purpose**

- ➢ Quantifies impact of disruptions in different operational phases of a tokamak plasma discharge

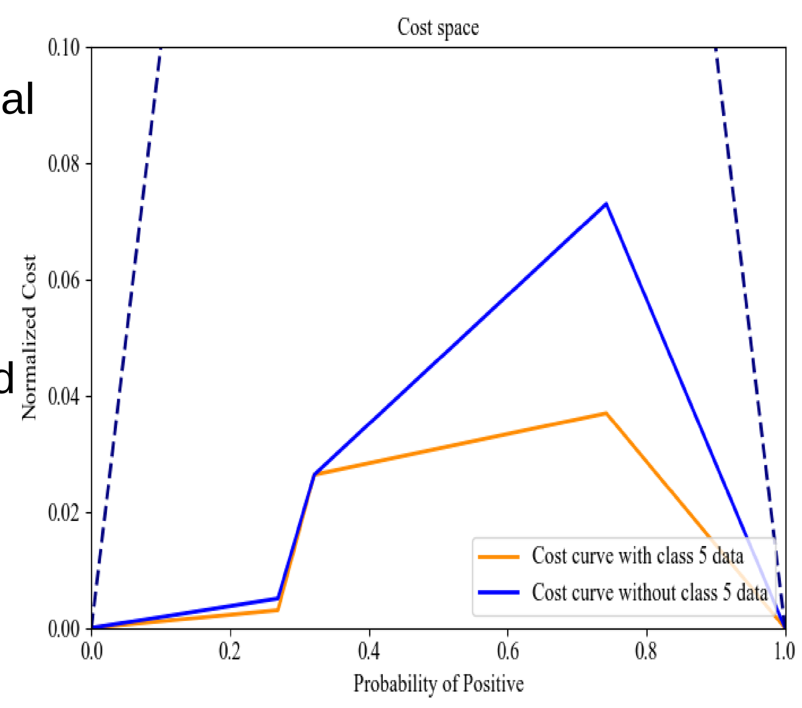
☐ **Method**

$$DBC = \begin{cases} \dfrac{Ip - Ip_{min}}{Ip_{std}} + \dfrac{Bt - Bt_{min}}{Bt_{std}} & potential\ DBC; \\ \dfrac{Ip - Ip_{min}}{Ip_{std}} + \dfrac{Bt - Bt_{min}}{Bt_{std}} + \dfrac{Ptot - Ptot_{min}}{Ptot_{std}} + \dfrac{CQrate - CQrate_{min}}{CQrate_{std}} & potential\ DBC; \\ 0\ undisruption; \end{cases}$$

- ➢ Training set filtering by DBC improves general-ization.

☐ **Cost Curve Evaluation**

- ➢ Models trained with high-DBC shots removed perform better in high-risk phases.
- ➢ Normalized DBC cost complements AUC for model evaluation.



Conclusion

- ☐ Anomaly detection transfer method: Enables disruption prediction from the first shot.
- ☐ PhyDANet method : Balances physics and data-driven learning.
- ☐ DBC framework : Provides risk-aware model evaluation and training.
- ☐ Layered strategy ensures safety and adaptability throughout all toka-mak lifecycle.

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