Machine Learning for Improved SRF Operation at CEBAF

Chris Tennant | *Jefferson Lab*

3rd ICFA Beam Dynamics Mini-Workshop on Machine Learning Applications for Particle Accelerators
Chicago, IL
November 1-4, 2022

Outline

- ***Introduction and Motivation***
- ***C100 Cavity Fault Classification***
- ***C100 Cavity Fault Prediction***
- ***Other***
  - ✓ Field Emission Management
  - ✓ Legacy Cavity Instability Detection
- ***Data Sources***
- ***Summary***

Acknowledgements

A. Carpenter, R. Suleiman, D. Turner, L. Vidyaratne*

Jefferson Laboratory

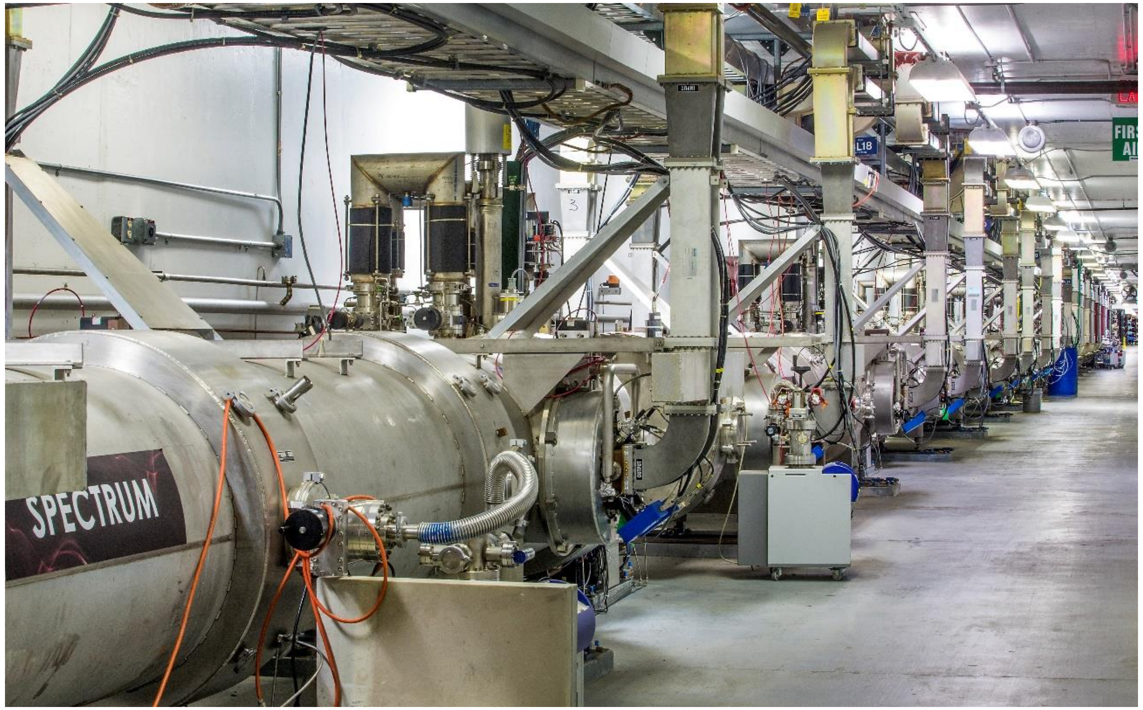
K. Ahammed, H. Ferguson, Md. M. Rahman, K. Iftekharuddin, J. Li

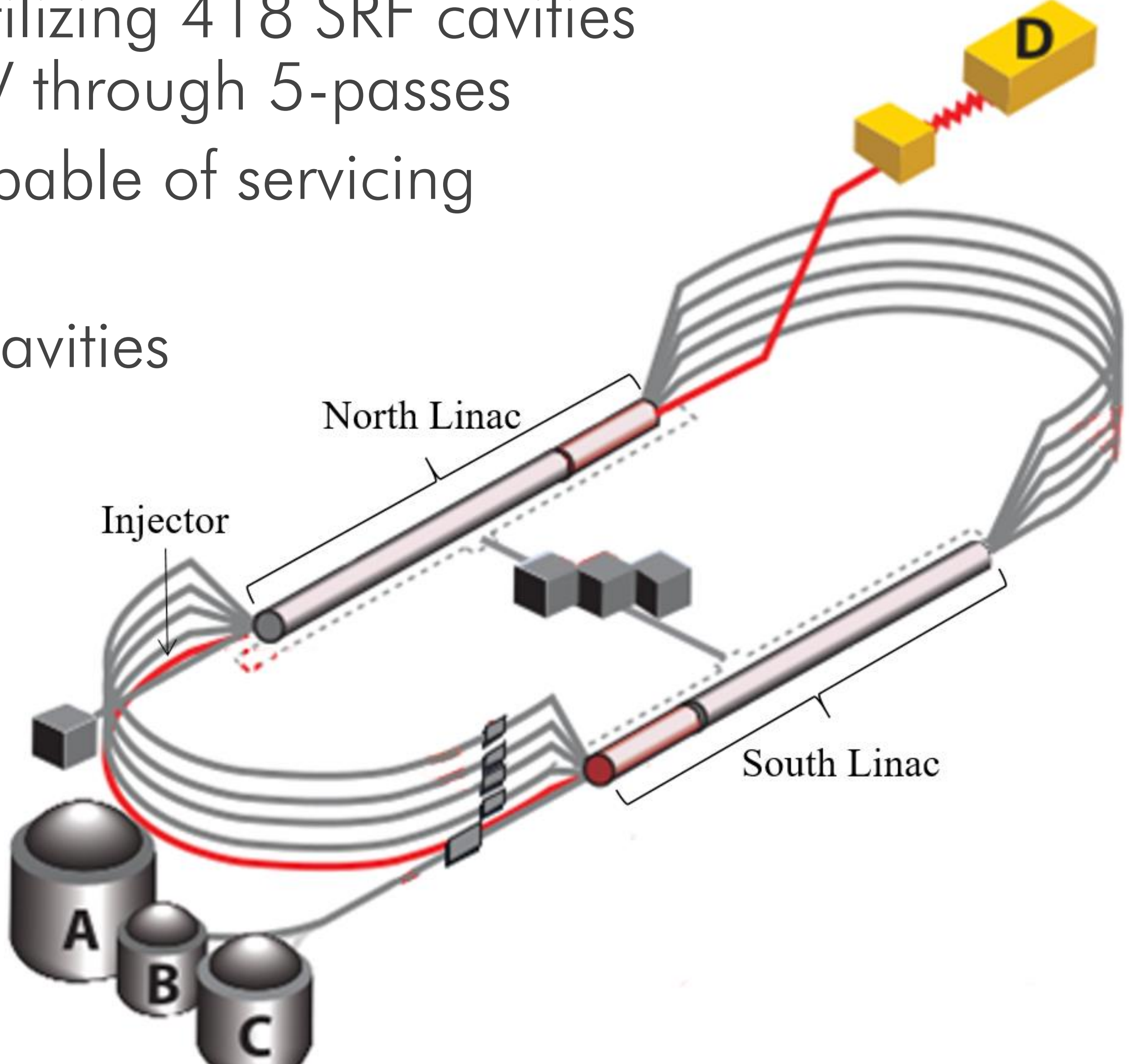
Old Dominion University

**now at Hitachi USA*

Continuous Electron Beam Accelerator Facility

- CEBAF is a CW recirculating linac utilizing 418 SRF cavities to accelerate electrons up to 12 GeV through 5-passes
- it is a nuclear physics user-facility capable of servicing 4 experimental halls simultaneously
- the heart of the machine is the SRF cavities

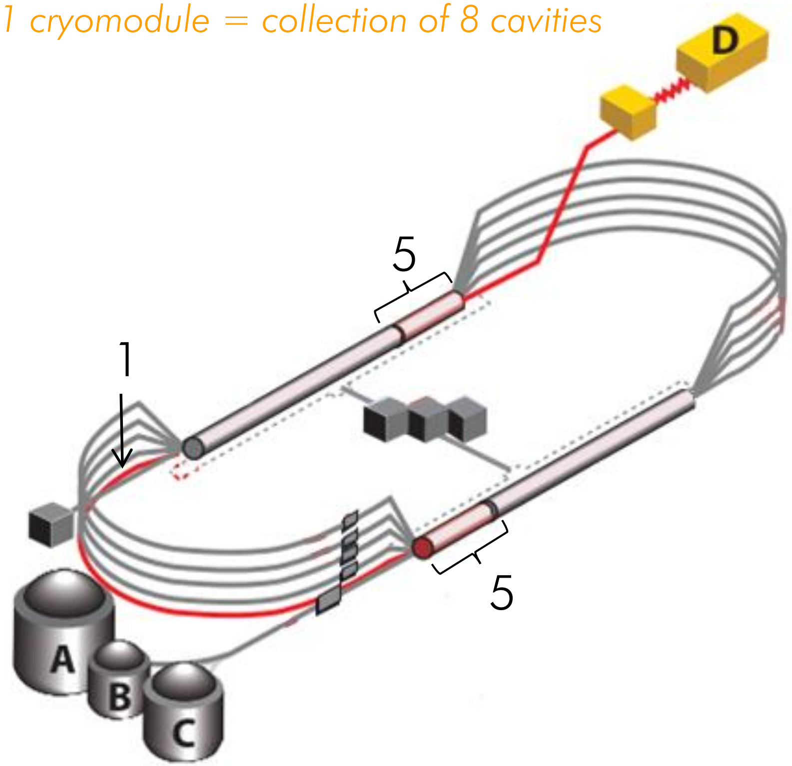




Fault Classification: Defining the Problem

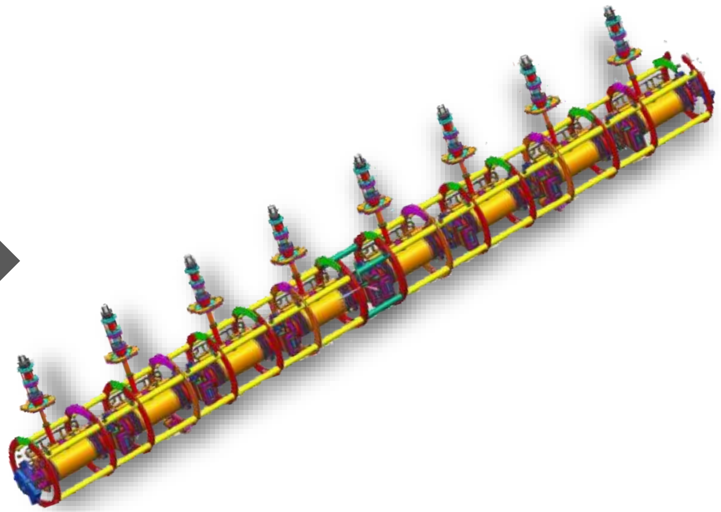
we have the ability to record high-fidelity data from 12 cryomodules

1 cryomodule = collection of 8 cavities



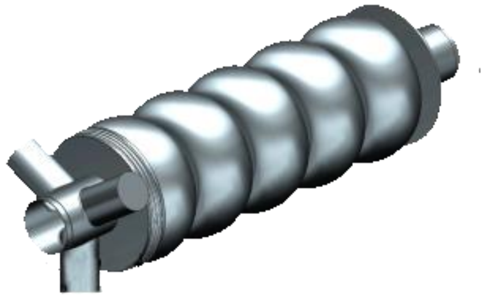
Question #1
Which of the 8 cavities faulted first?

17 signals/cavity × 8 cavities = 136 signals



Question #2
What kind of trip was it?

17 signals



train a model to correctly classify the <u>cavity</u> and <u>type</u> of RF fault given waveform data

Motivation for Machine Learning

- laborious for subject matter expert to hand label thousands of events

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Post-Run Analysis

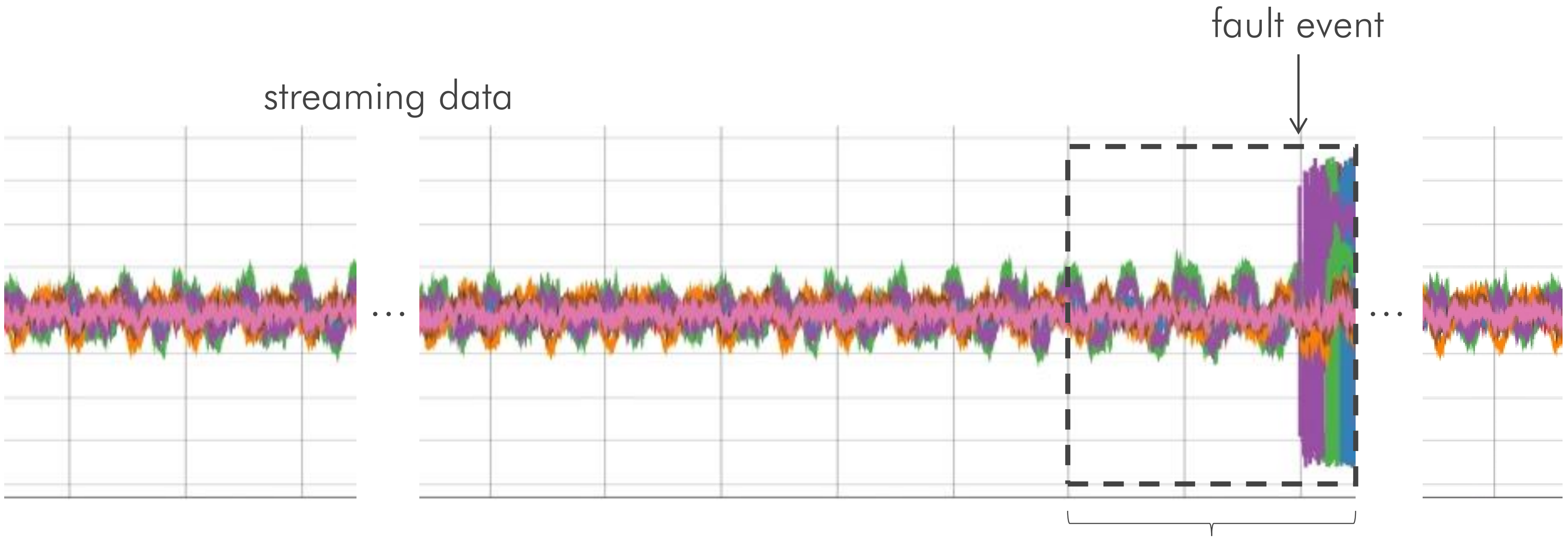
- use aggregate statistics for data-driven guidance for maintenance and/or upgrade activities
  - ✓analysis of fall 2018 data indicated three cryomodules in the South Linac were prone to microphonic-based faults → provided justification to perform microphonics hardening (installing tuner dampers) → reduced microphonics-based trip rates → gradients could be increased in those cryomodules

Post-Fault Analysis

- provides critical feedback to control room operators
- fault types get mapped to actions for the operators
  - ✓"if Trip A happens X times within Y minutes, drop gradient in the cavity by Z MV/m"

Data: Waveform Harvester

- waveform harvester was developed to capture RF time-series signals after a fault and write them to file for later analysis
  - ✓ each of the 17 harvested waveform signals is 8,192 points long
  - ✓ trigger set such that 94% of the recorded data precedes the fault and 6% after
  - ✓ pre-fault data provides valuable information about the root cause of the trip



8,192 samples × 0.2 ms/sample = 1.64 seconds

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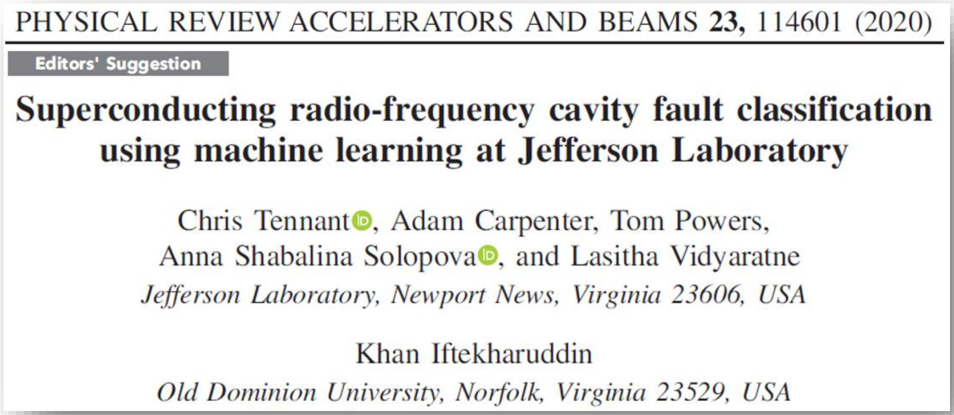
ML Model Performance

- models were applied to data collected from March 10-24, 2020
  - ✓ physics run was prematurely ended due to COVID-19
- 312 fault events were analyzed by the models
- summary of model performances compared to labeled data

	Agree	Disagree	Total
Cavity Model	265	47	312
Fault Model	244	68	312

- cavity model accuracy: 84.9%
  - ✓ testing accuracy: 87.9%
- fault model accuracy: 78.2%
  - ✓ testing accuracy: 87.7%


PHYSICAL REVIEW ACCELERATORS AND BEAMS **23,** 114601 (2020)

Editors' Suggestion

Superconducting radio-frequency cavity fault classification using machine learning at Jefferson Laboratory

Chris Tennant, Adam Carpenter, Tom Powers,
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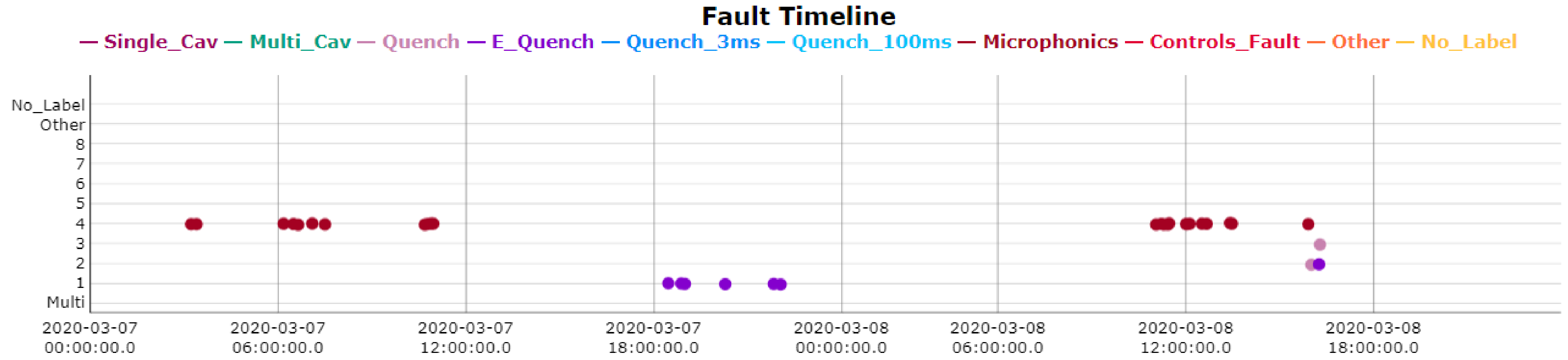
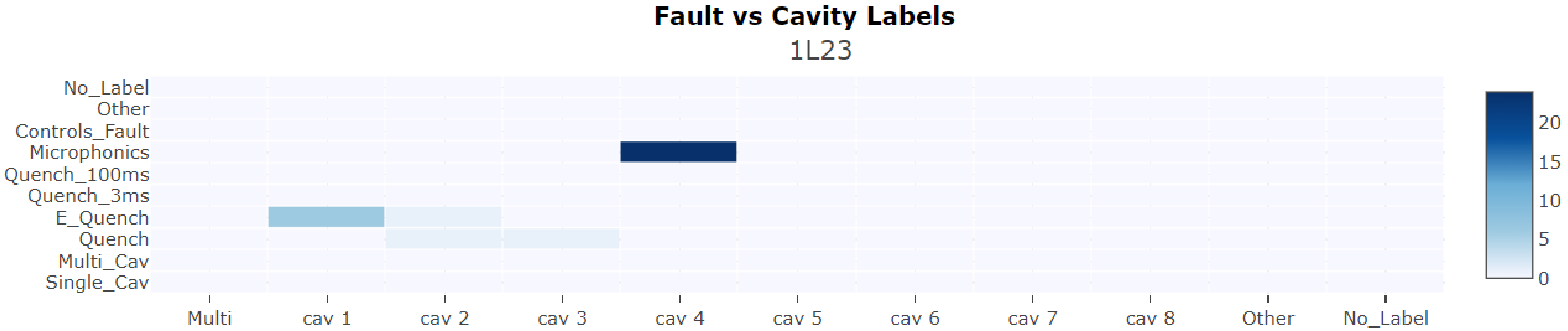
Khan Iftekharuddin
Old Dominion University, Norfolk, Virginia 23529, USA

Visualization and Communication

- for ML models to be effective, information must be communicated clearly and concisely
- visualize spatial and temporal nature of model predictions





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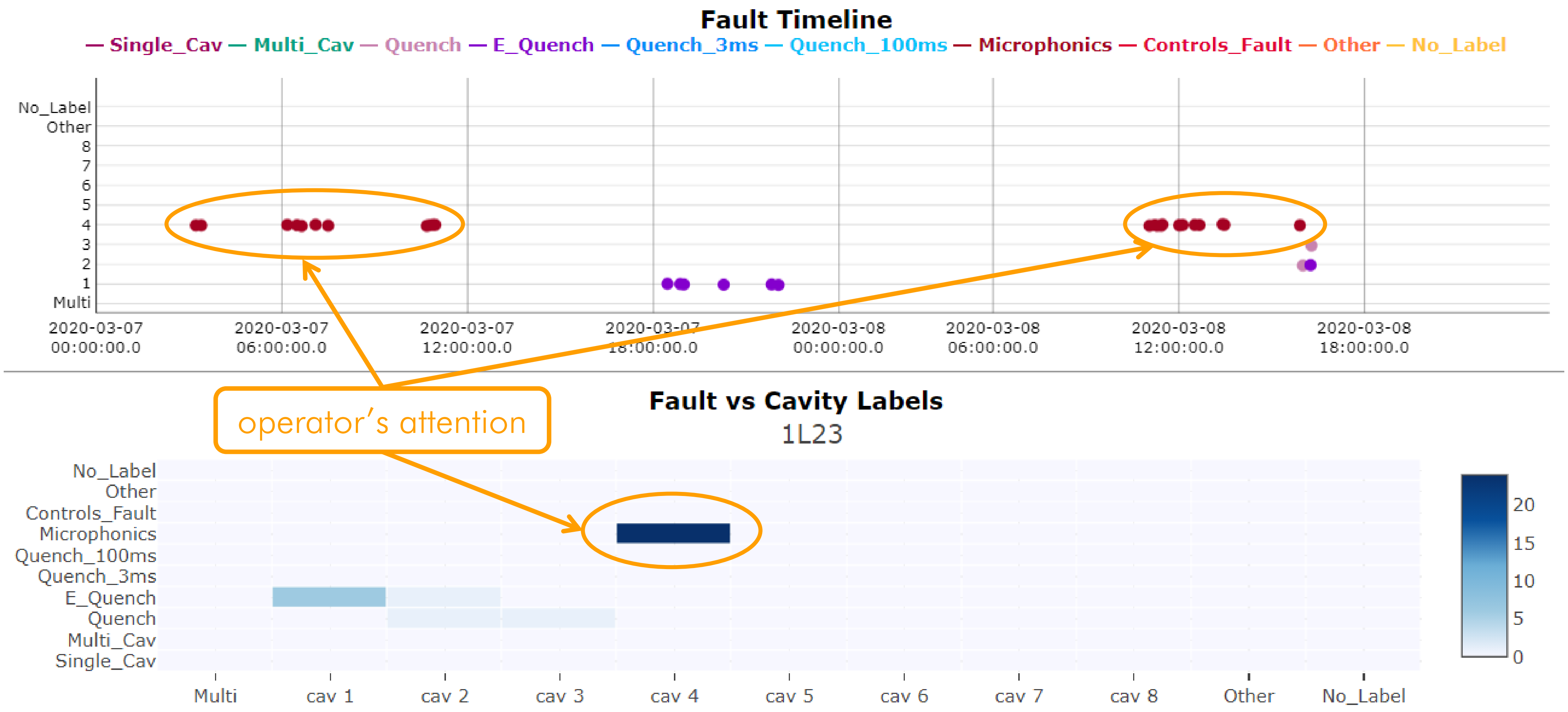
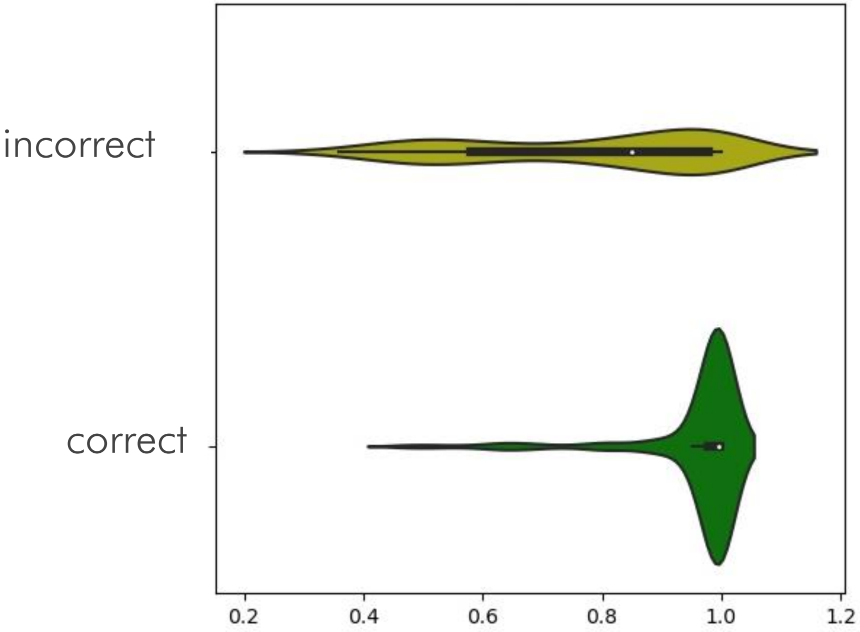
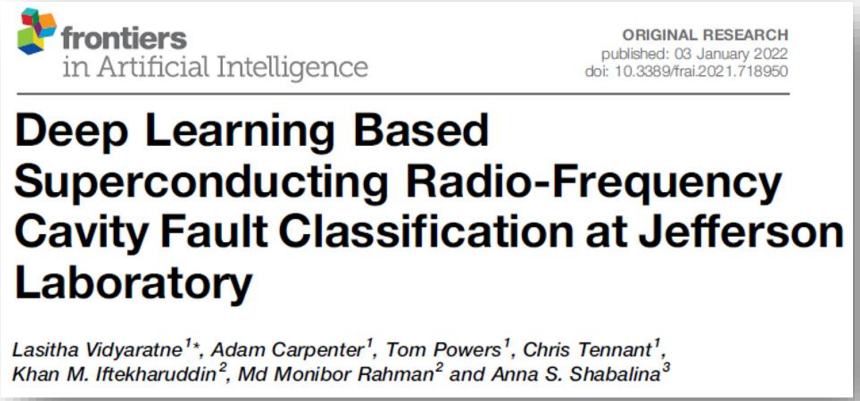


Machine Learning → Deep Learning

- benefits
  - ✓ avoid feature extraction
  - ✓ computationally faster (needful for fault prediction)
  - ✓ allow for uncertainty quantification




frontiers in Artificial Intelligence

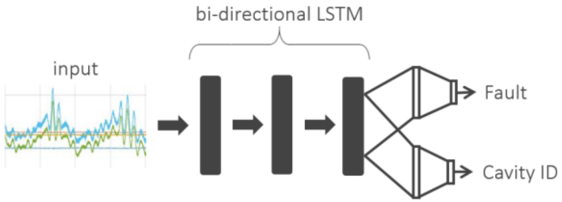
ORIGINAL RESEARCH
published: 03 January 2022
doi: 10.3389/frai.2021.718950

Deep Learning Based Superconducting Radio-Frequency Cavity Fault Classification at Jefferson Laboratory

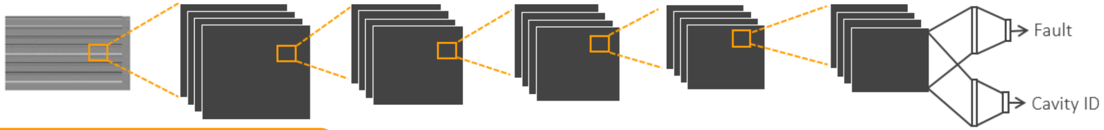
Lasitha Vidyaratne[1], Adam Carpenter[1], Tom Powers[1], Chris Tennant[1], Khan M. Iftekharuddin[2], Md Monibor Rahman[2] and Anna S. Shabalina[3]*

Machine Learning → Deep Learning

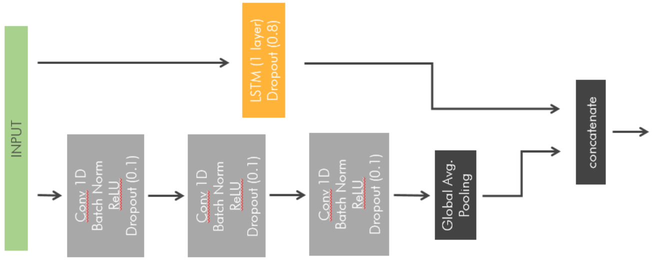
- benefits
  - ✓ avoid feature extraction
  - ✓ computationally faster (needful for fault prediction)
  - ✓ allow for uncertainty quantification
- architectures explored
  - ✓ recurrent NN

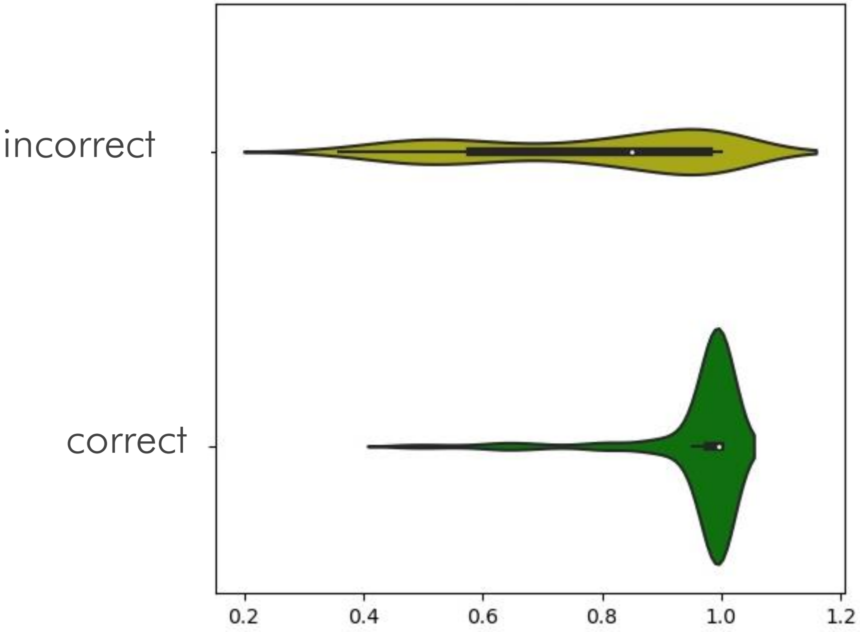


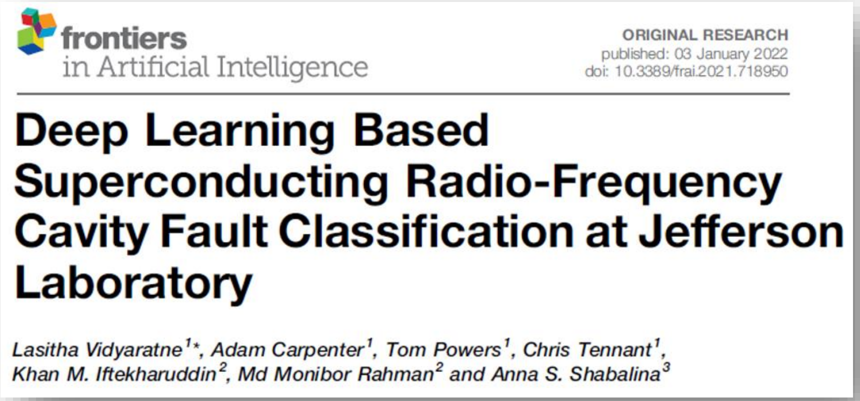
  - ✓ CNN



  - ✓ LSTM + CNN



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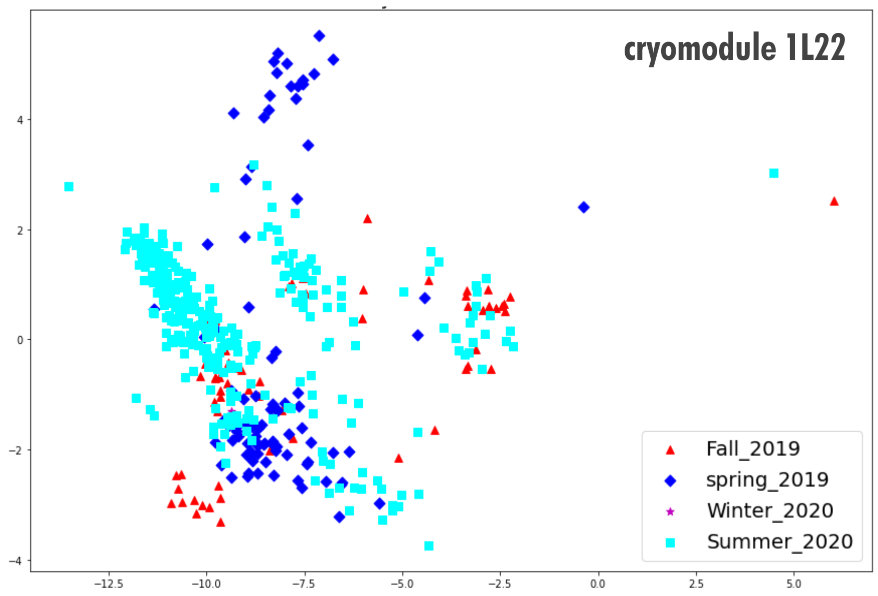
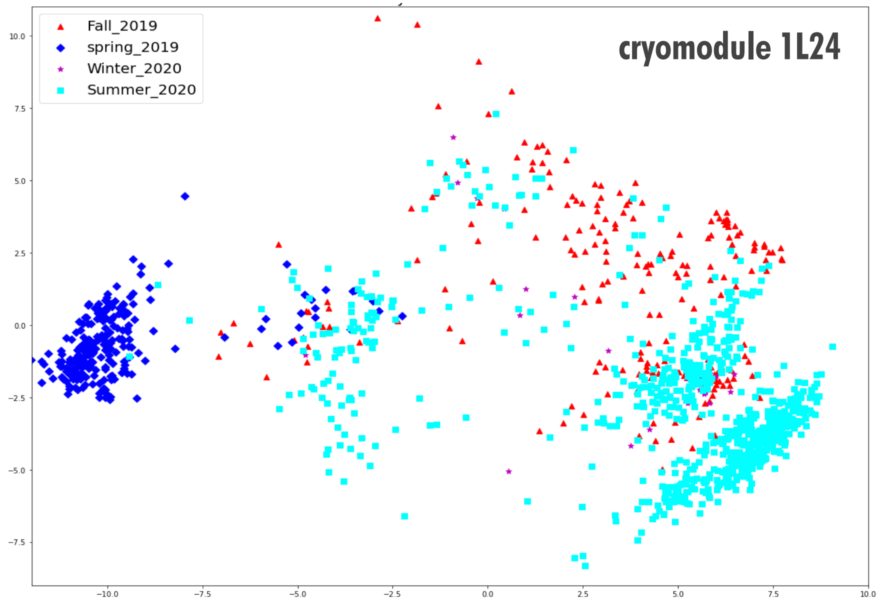
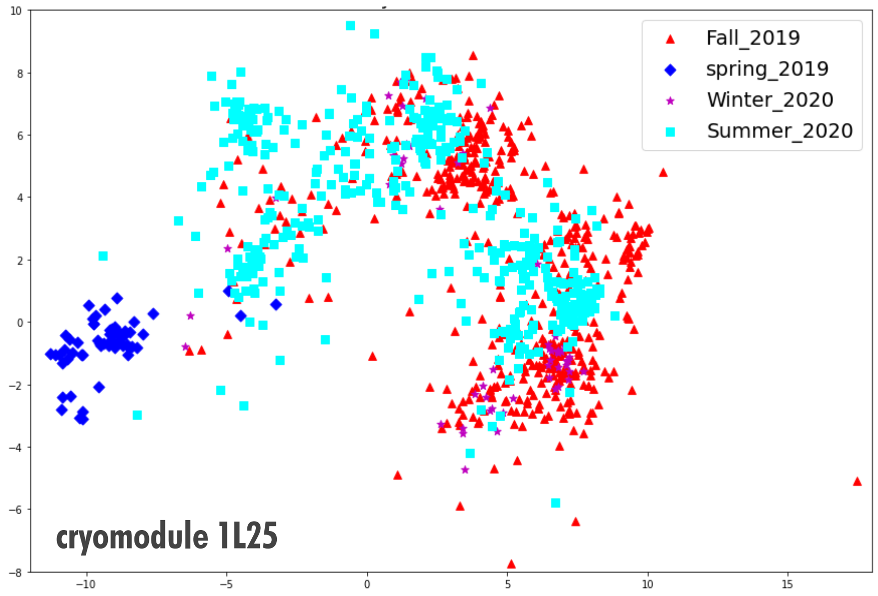
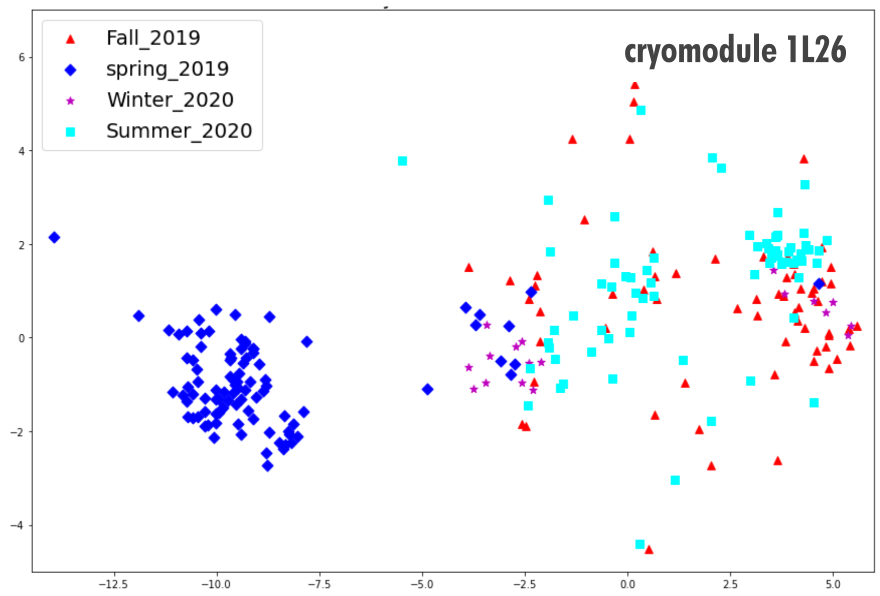
Dimensionality Reduction: Visualize Runs









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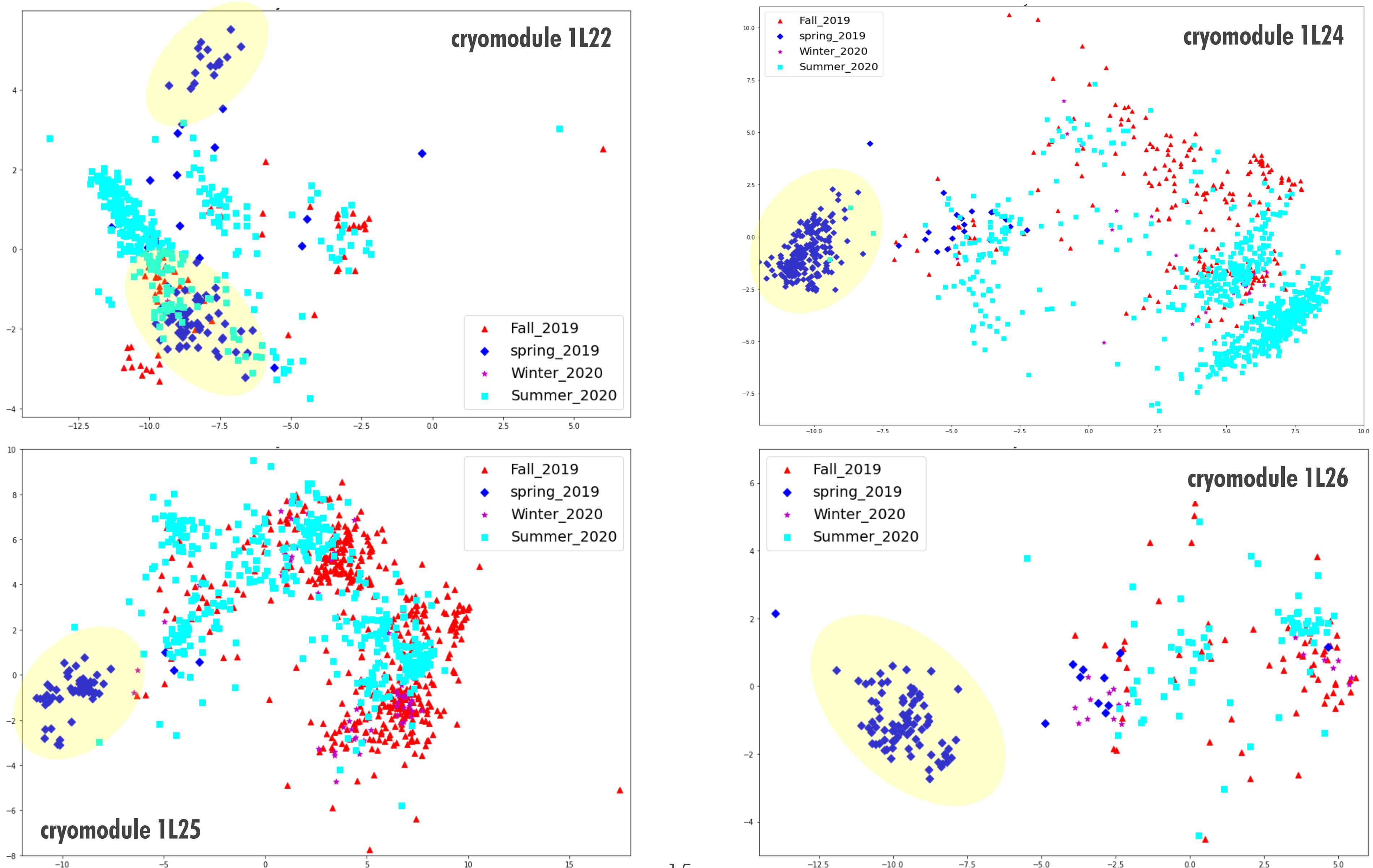

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Maintaining Model Performance

- most critical challenge is to maintain model performance from one operational run to the next *(work in progress)*

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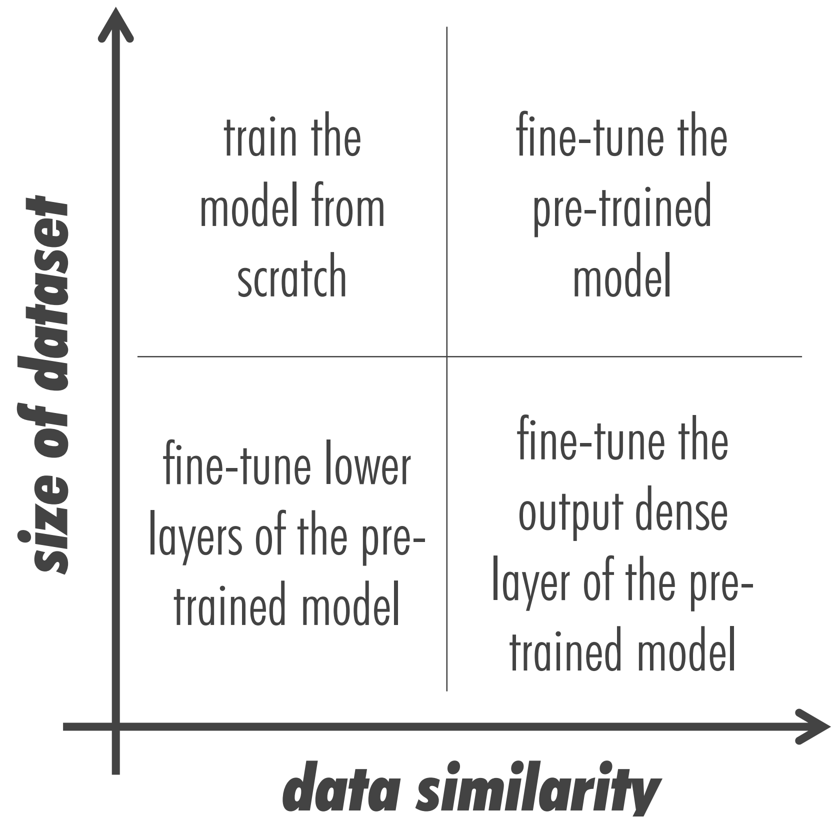
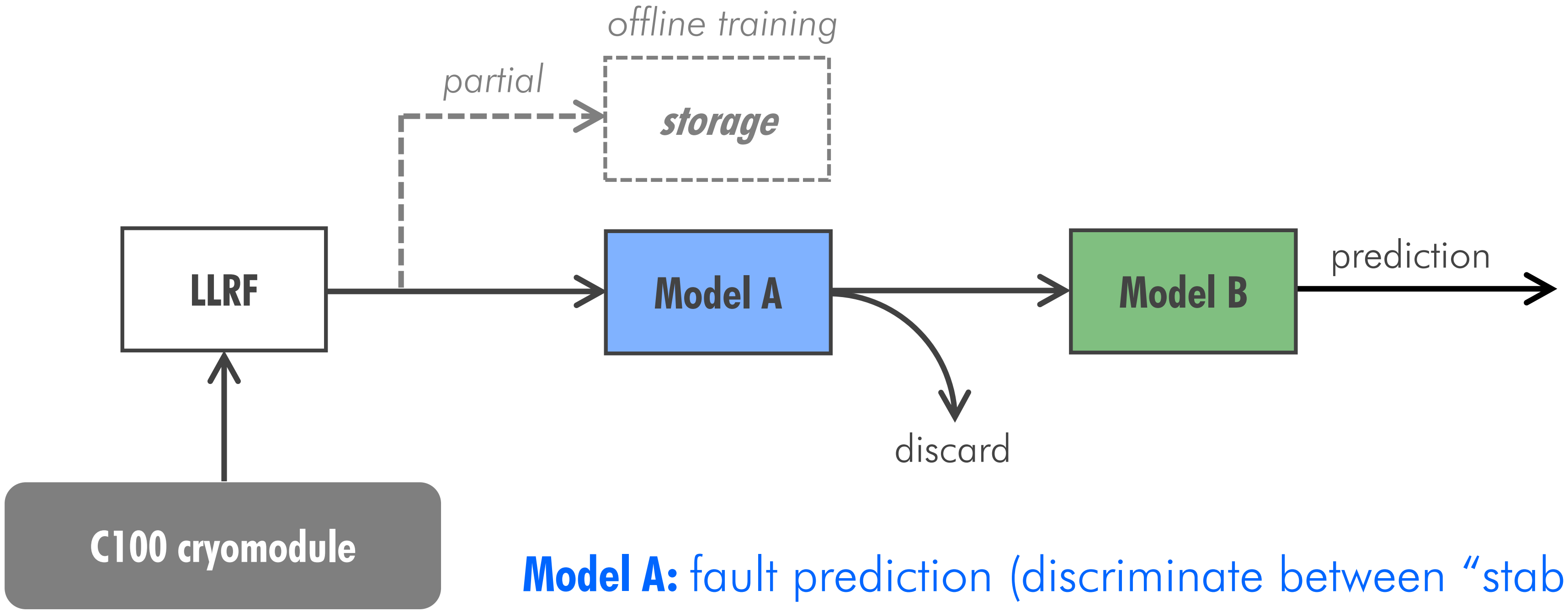
1. **Feature Extraction**
   Remove the output layer and use the entire network as a fixed feature extractor for the new dataset
2. **Fine-Tune a Pre-Trained Model**
   Fine-tune the weights of the pre-trained network (all layers)
3. **Train Some Layers While Freezing Others**
   Freeze weights of earlier layers and fine-tune the weights of later layers



https://tinyurl.com/yck4kzuk

Fault Classification → Fault Prediction

- small portion of waveforms around fault event are used for training classifiers
  - ✓uses *static* datasets
- modifications to LLRF system will allow us to continuously stream data
- investigate if data prior to fault contains enough information to predict event



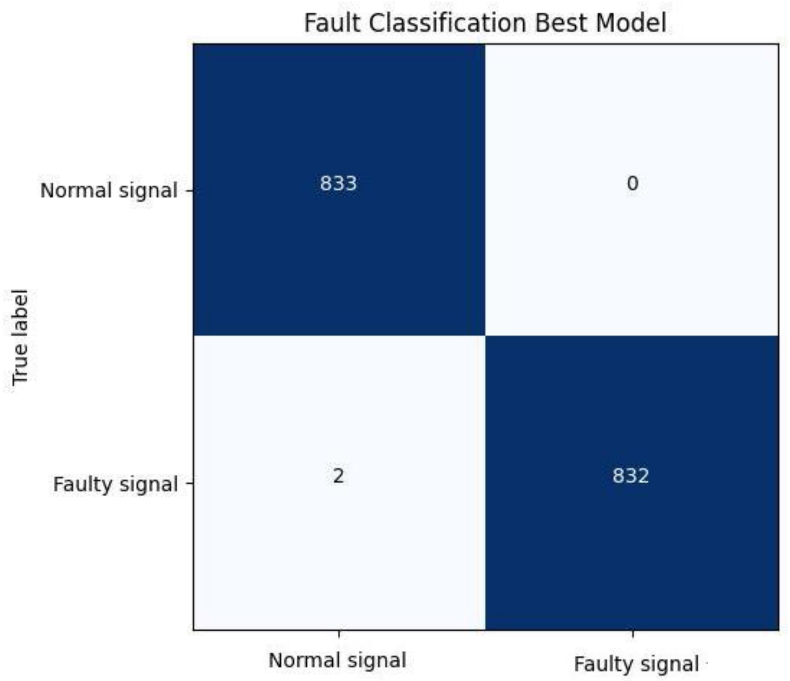
Model A: fault prediction (discriminate between "stable" and "impending")
Model B: fault-type prediction (classify fault)

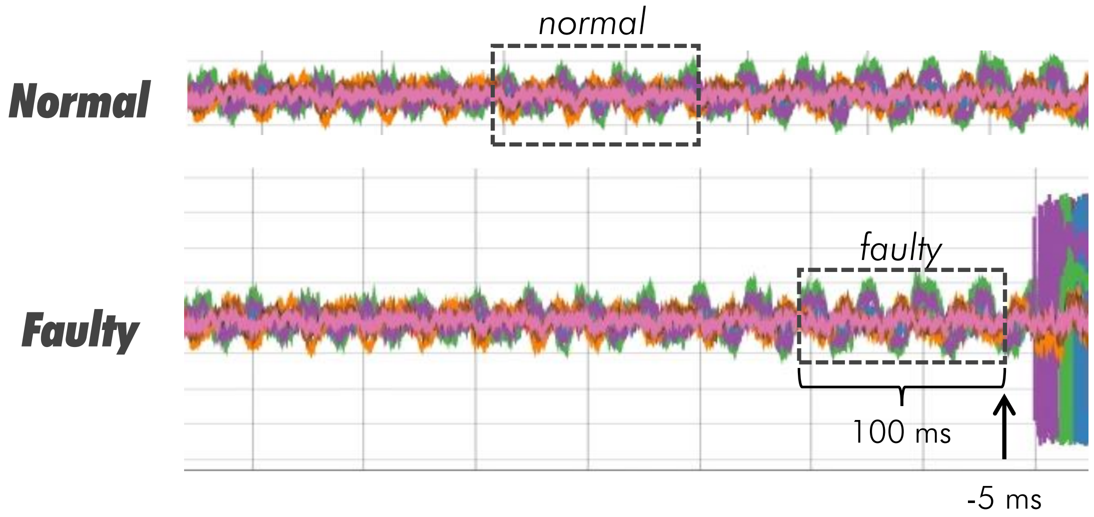
Model A: Binary Classifier

Model	Fault Types	Normal Signals	Fault Signals	Dataset	Experiment
CNN+LSTM	slow faults	"real" normal	t = -1435 ms	Datasets A,B,C	T.01
				Dataset D	T.02
			t = - 5 ms	Datasets A,B,C	T.03
				Dataset D	T.04
		"quasi" normal	t = -1435 ms	Datasets A,B,C	T.05
				Dataset D	T.06
			t = - 5 ms	Datasets A,B,C	T.07
				Dataset D	T.08
	fast faults	"real" normal	t = -1435 ms	Datasets A,B,C	T.09
				Dataset D	T.10
			t = - 5 ms	Datasets A,B,C	T.11
				Dataset D	T.12
		"quasi" normal	t = -1435 ms	Datasets A,B,C	T.13
				Dataset D	T.14
			t = - 5 ms	Datasets A,B,C	T.15
				Dataset D	T.16

- slow vs fast fault types
- "real" vs "quasi"-normal
- fault signal window
- dataset date

Model A: Binary Classifier





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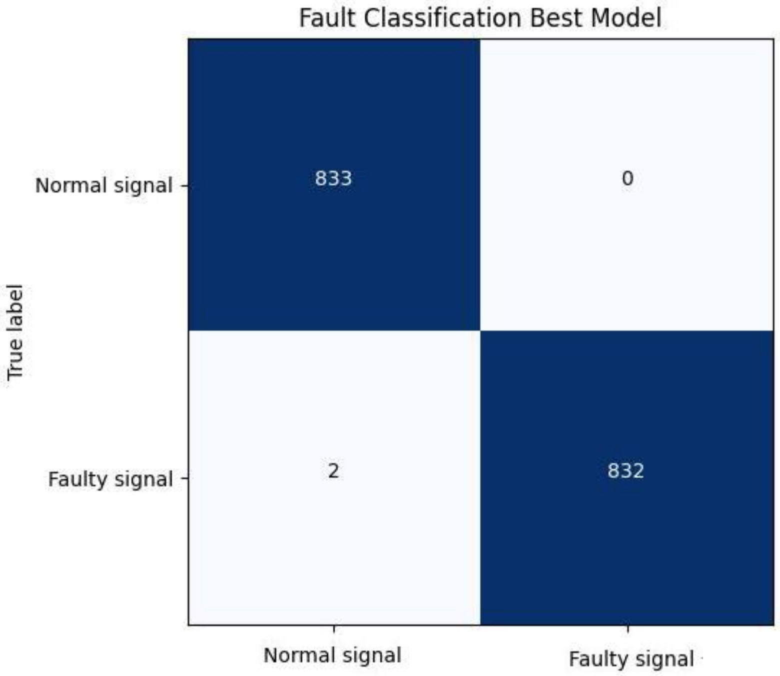
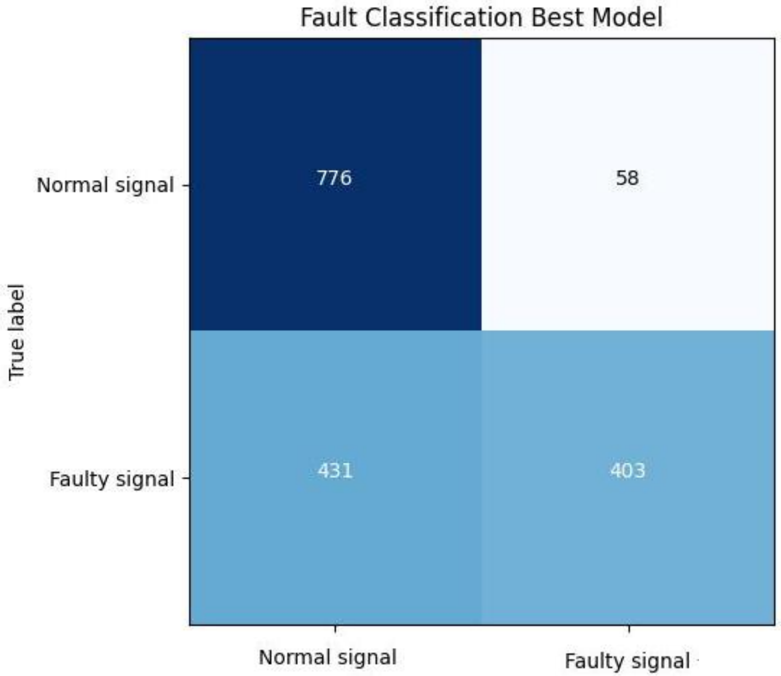
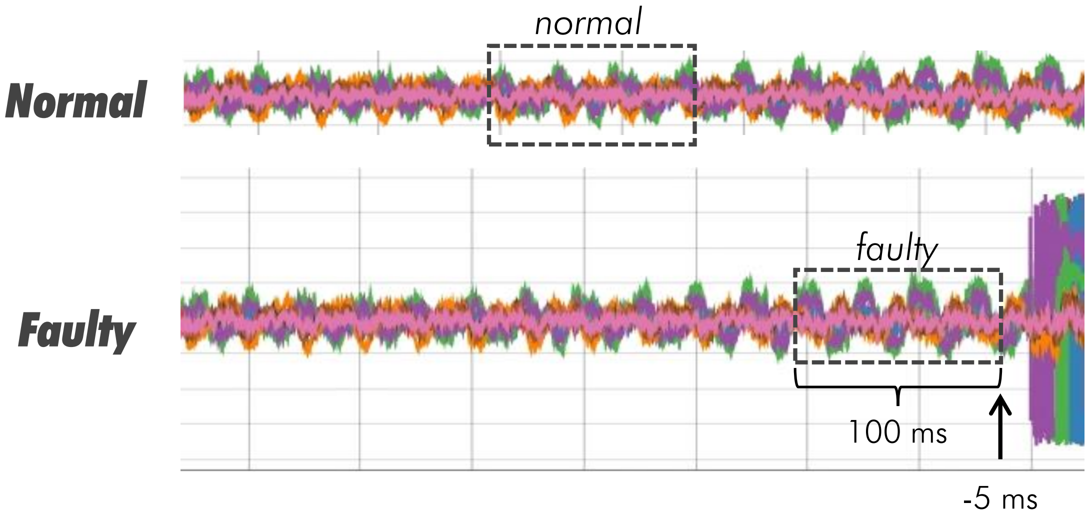
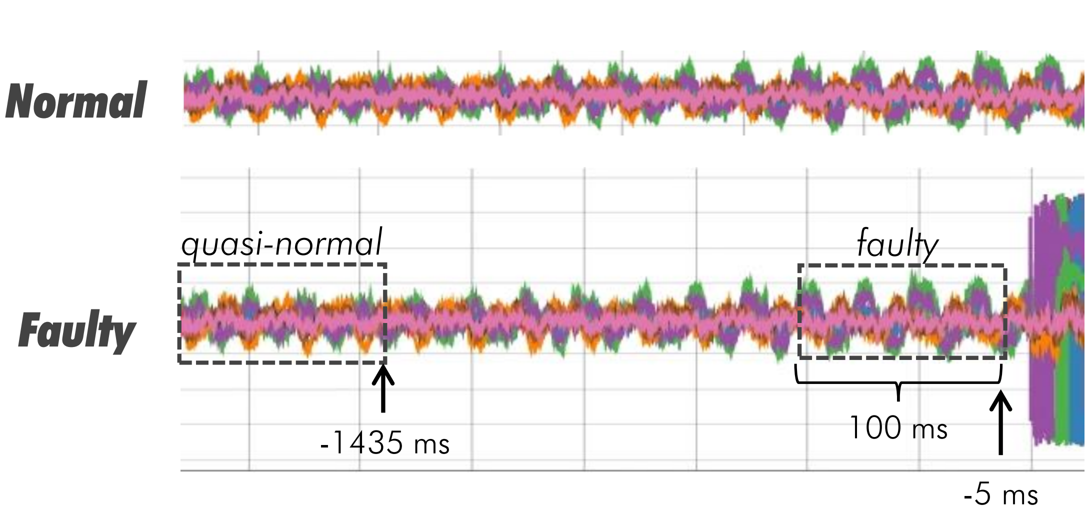
Model A: Binary Classifier



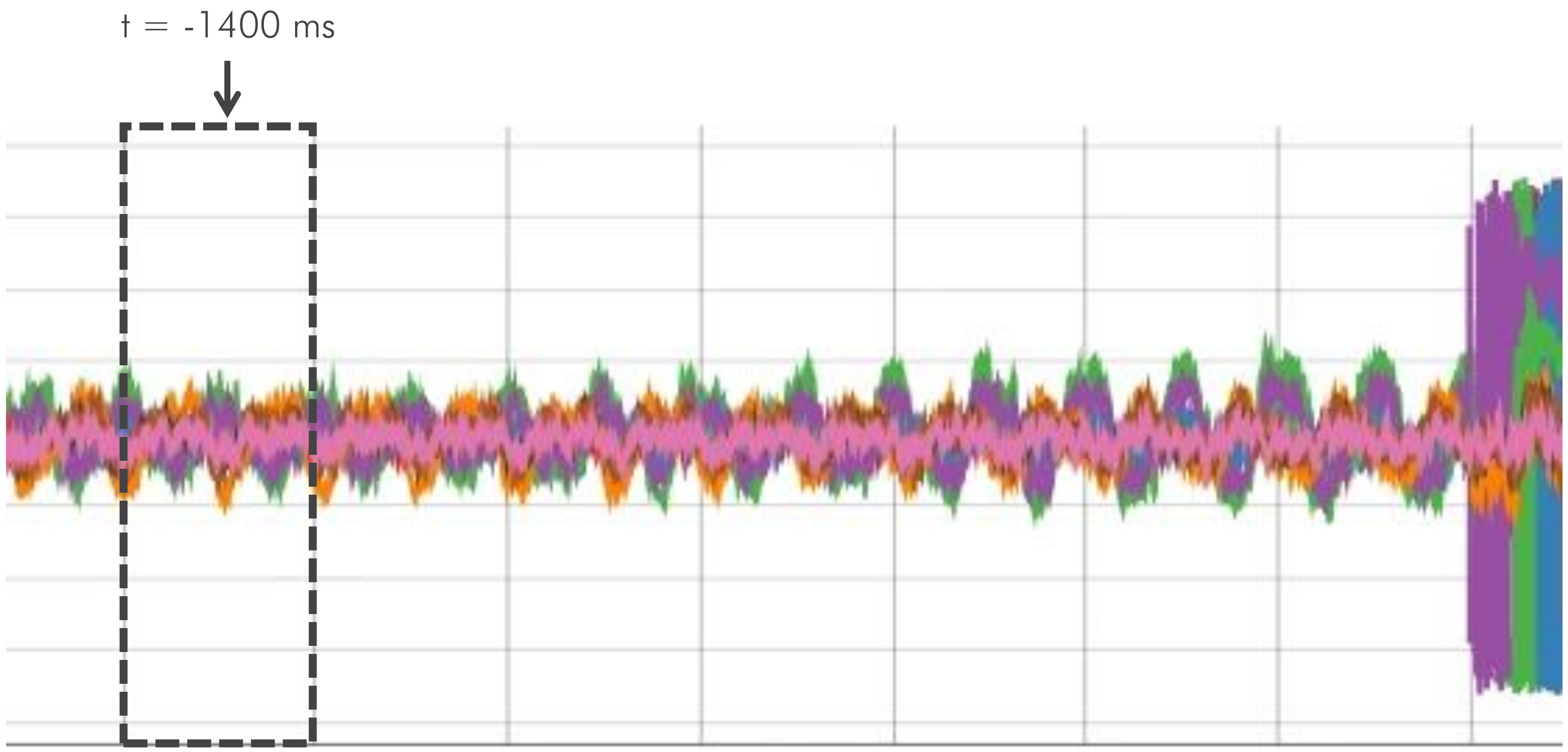






Model B: Fault Classifier

- can data prior to event accurately predict the fault type?
  - ✓ use saved waveforms



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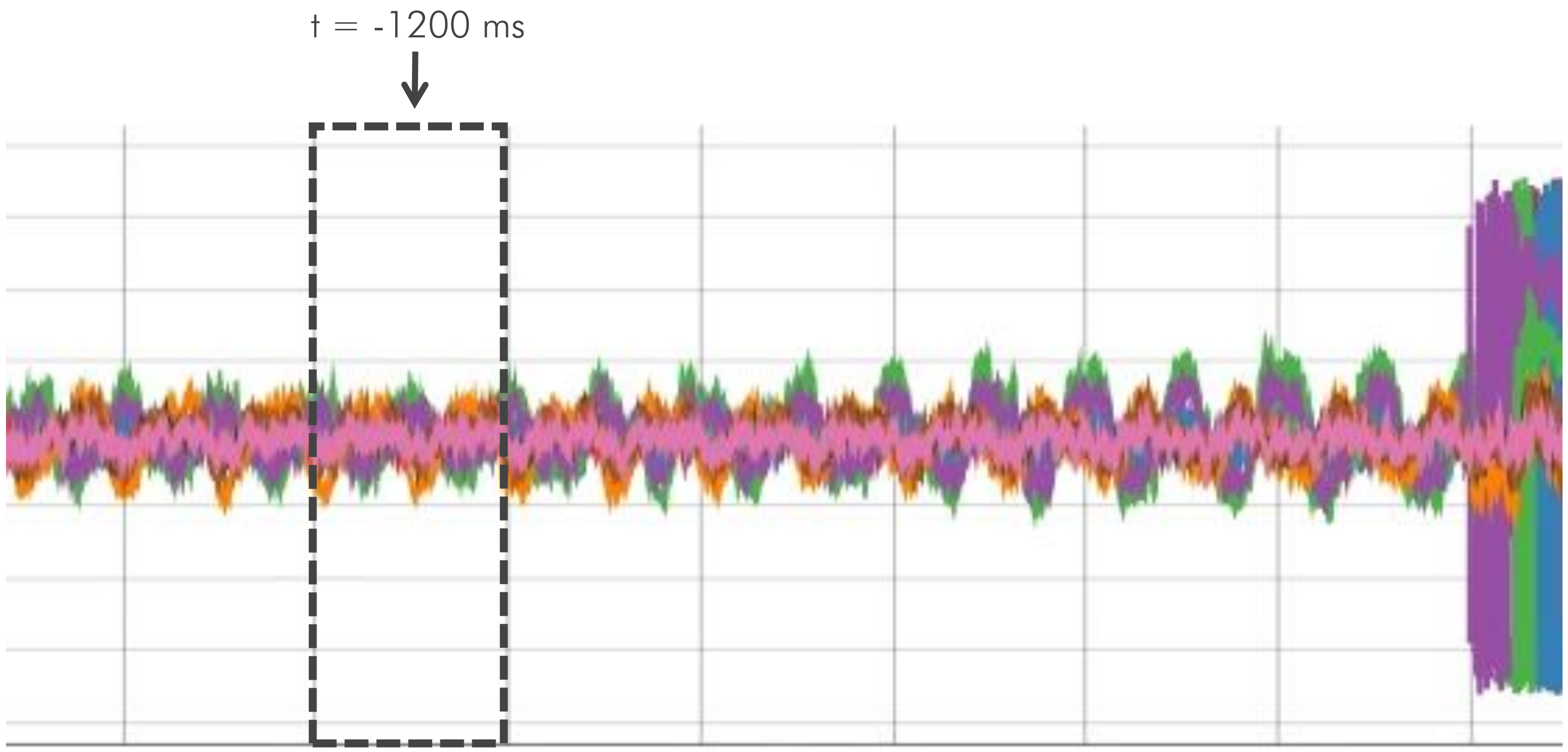

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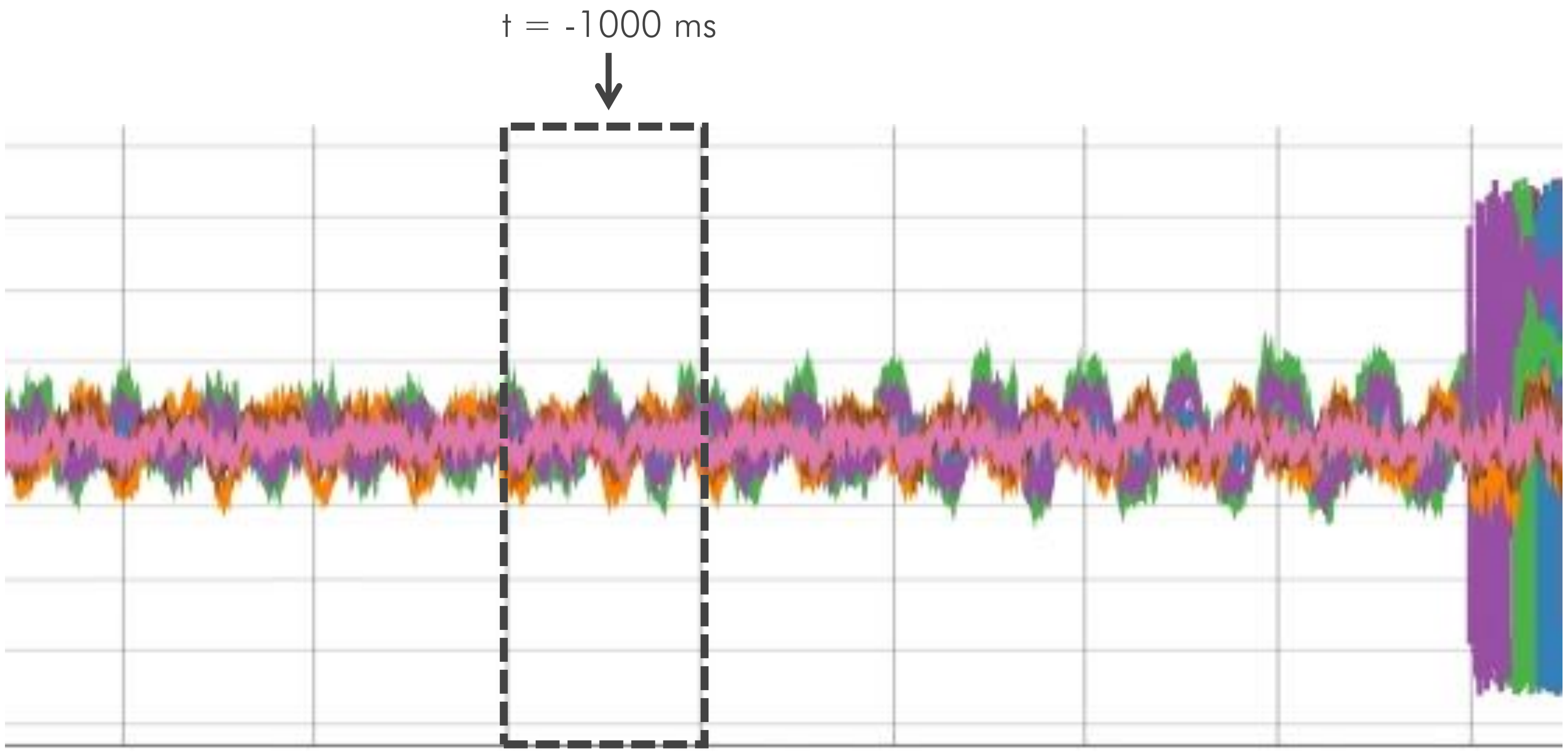

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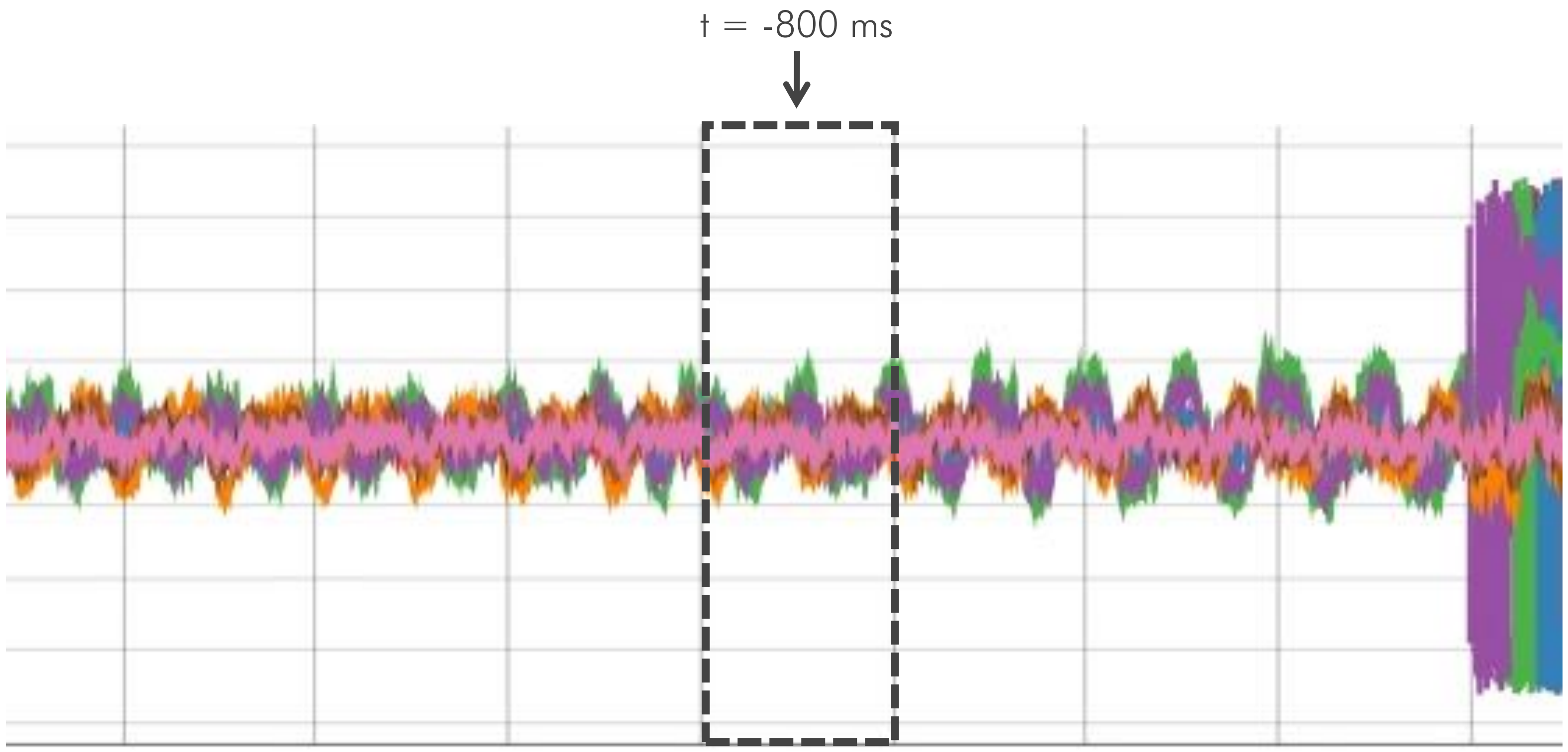

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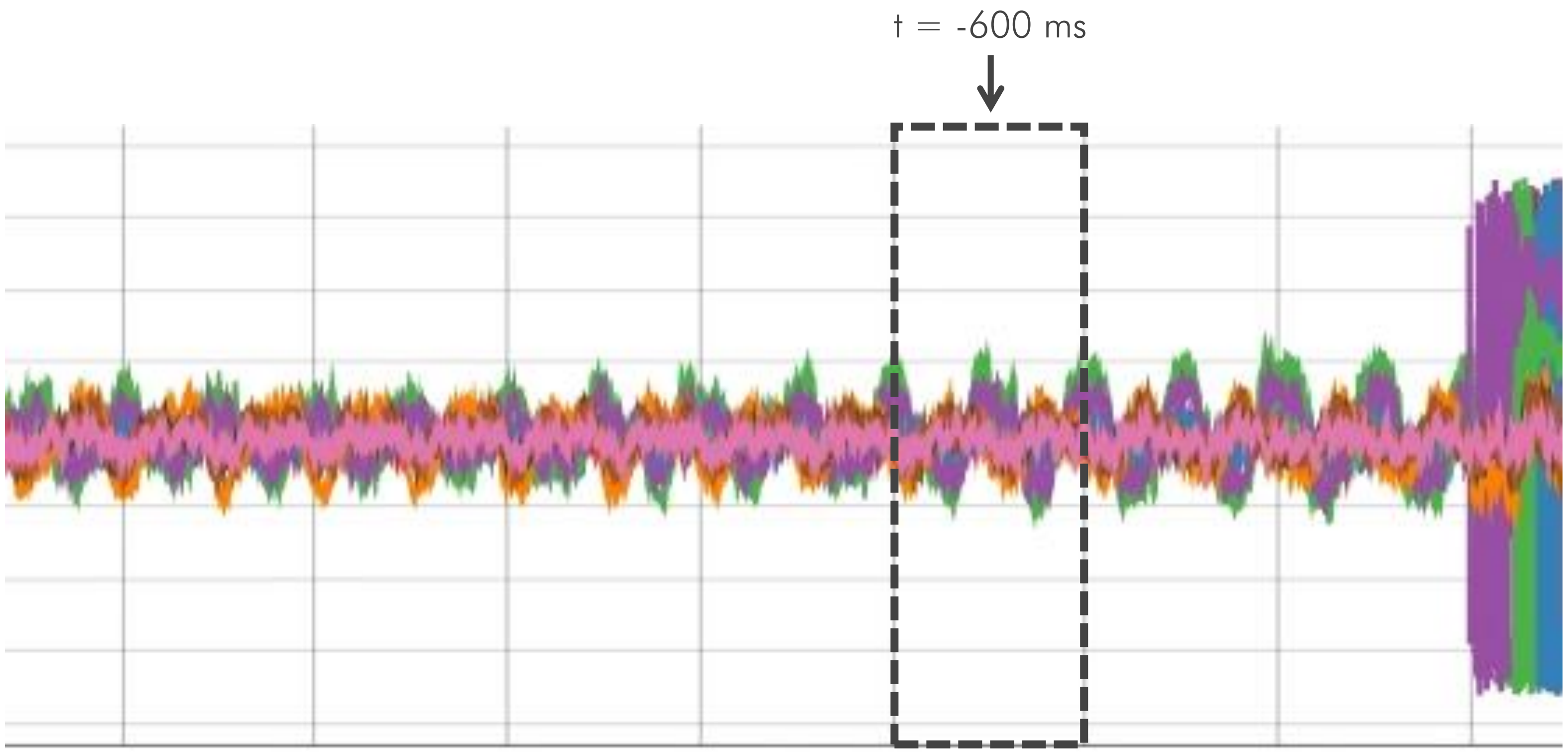

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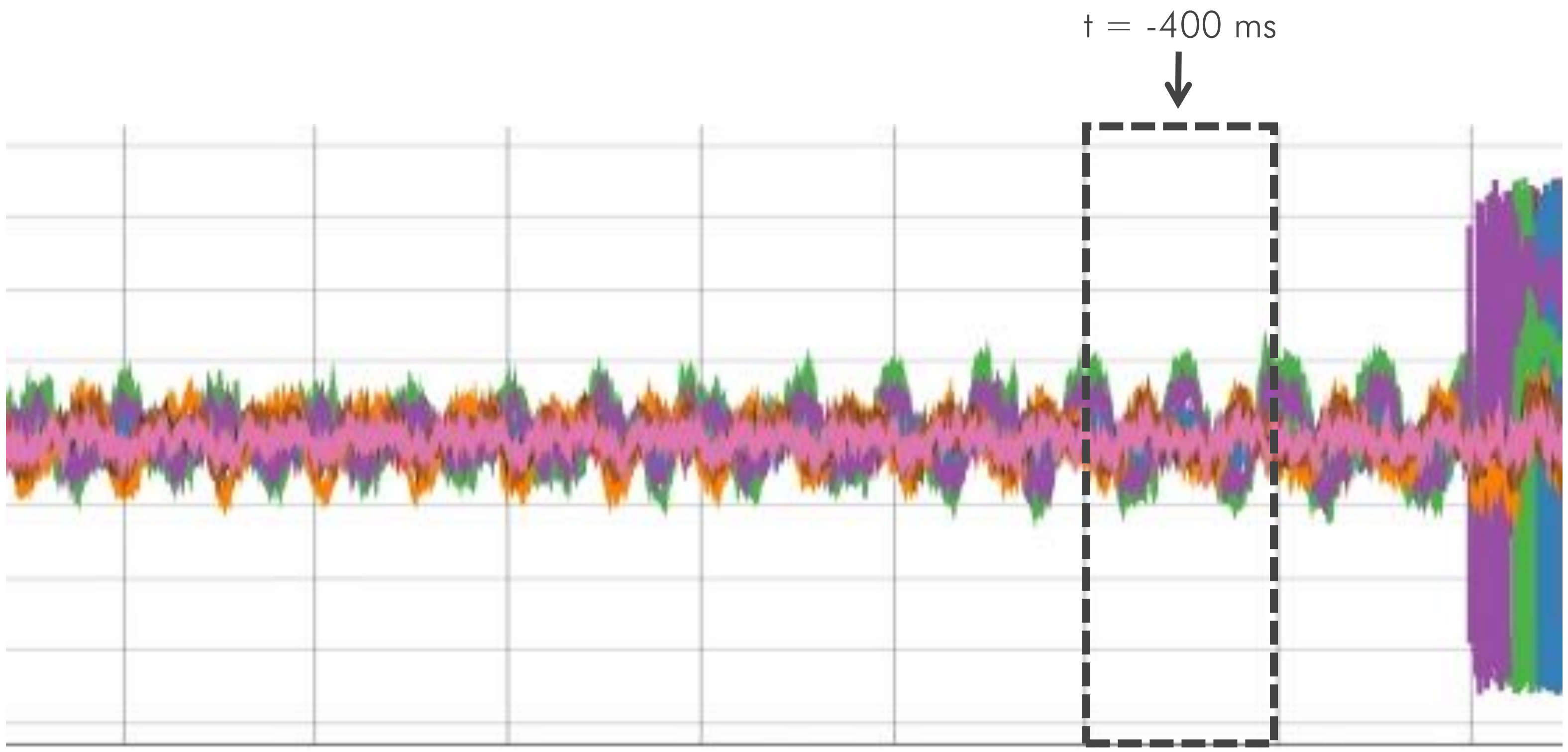

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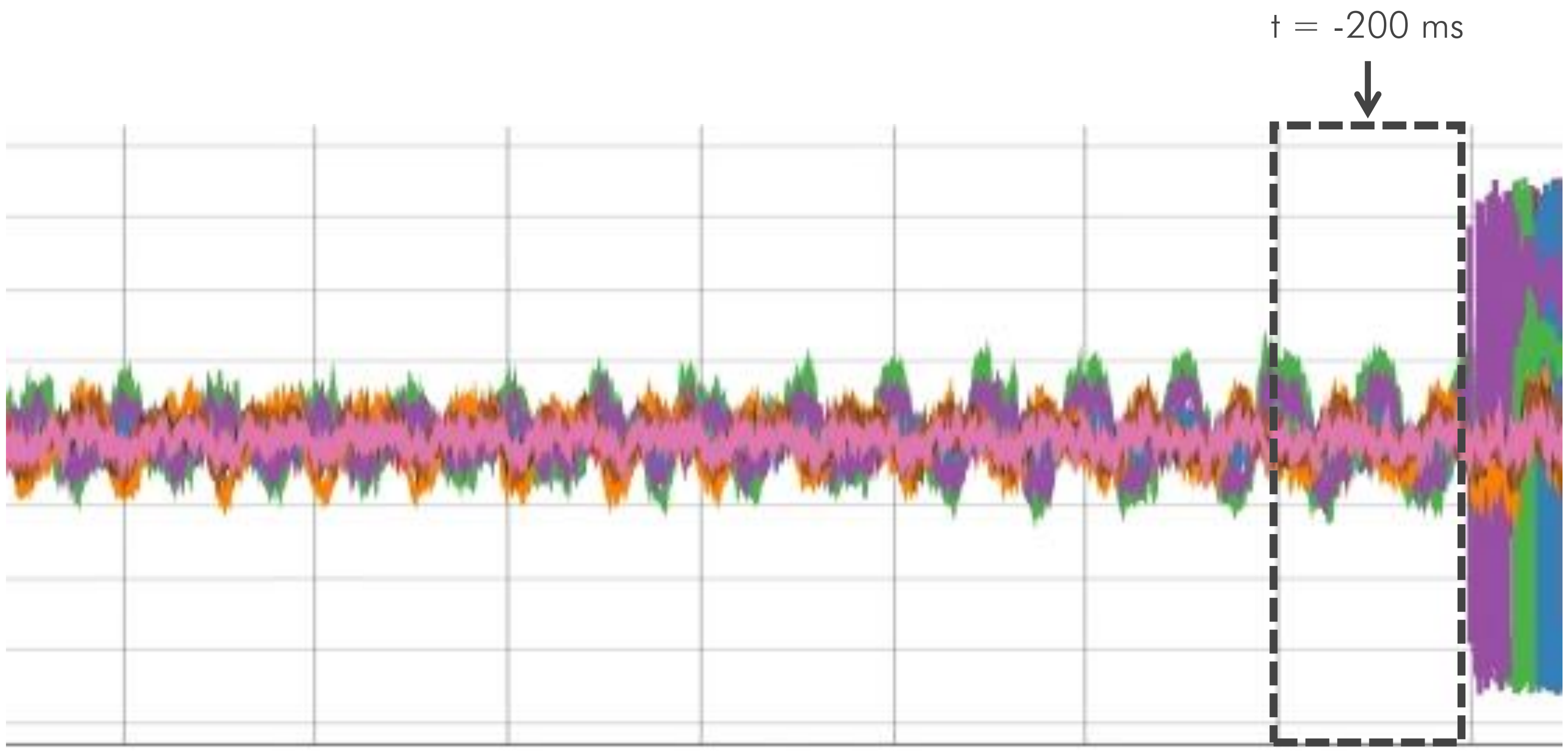

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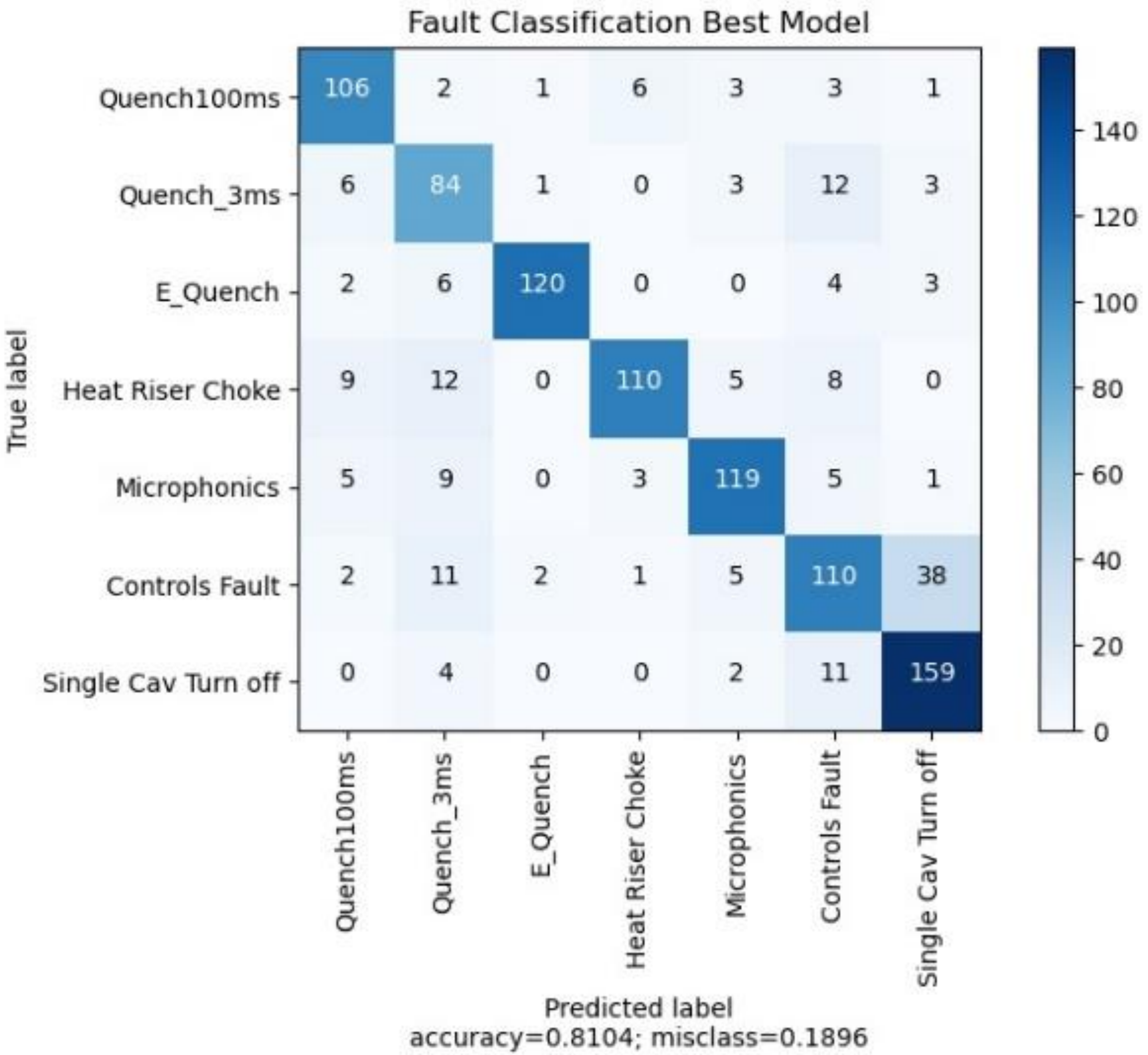
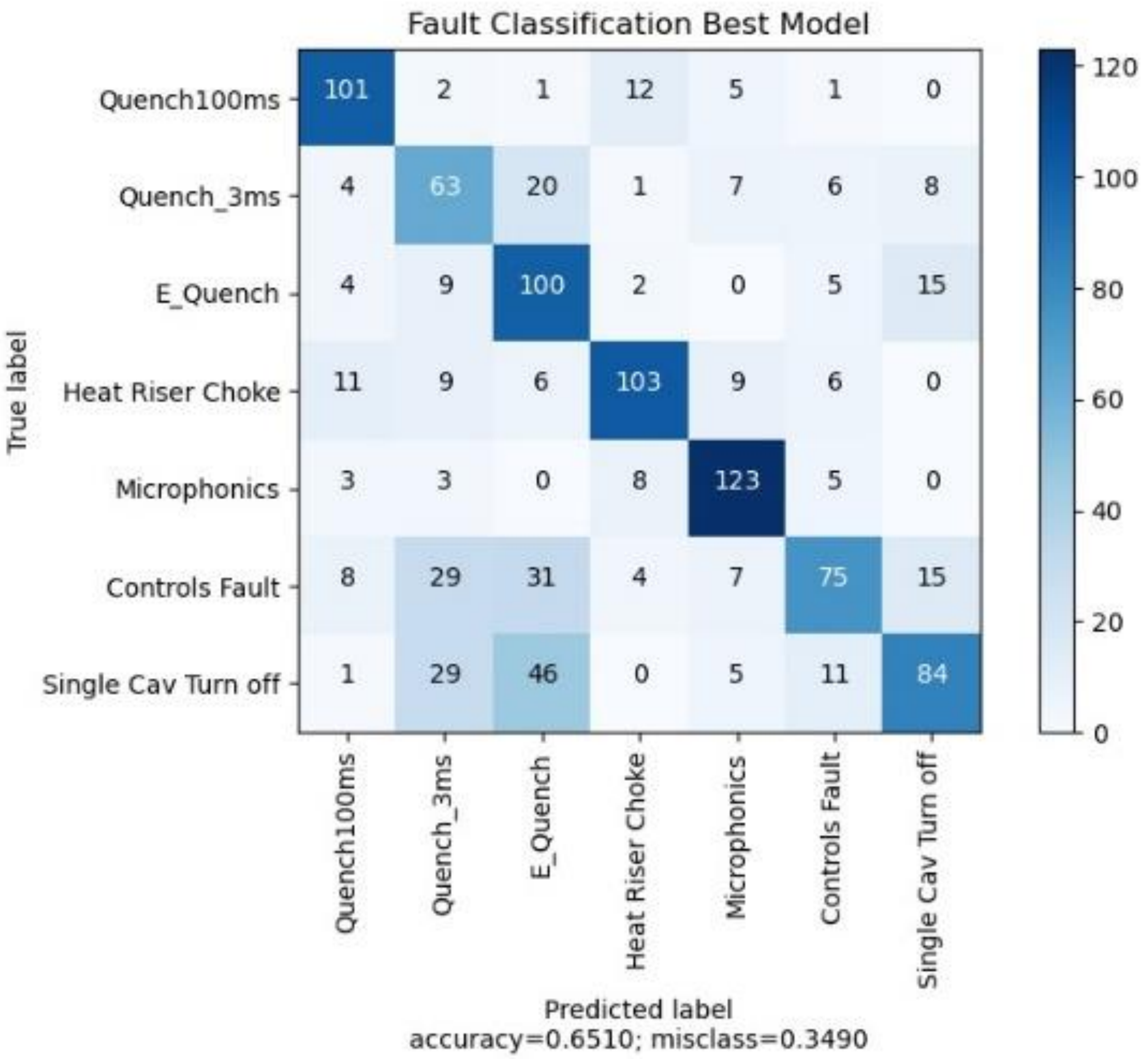
Model B: Fault Classifier

0 ms prior to fault



Model B: Fault Classifier

20 ms prior to fault



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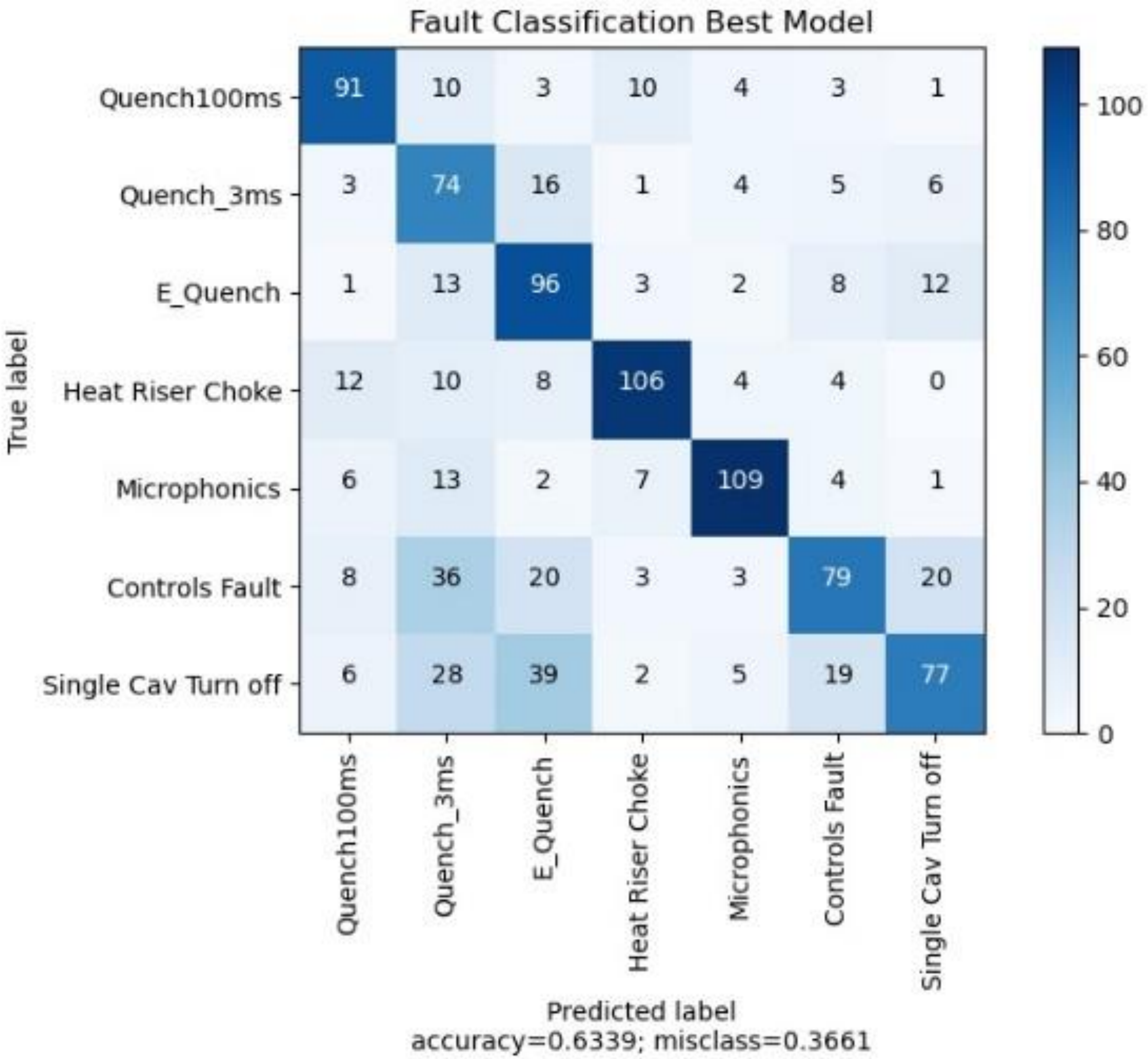
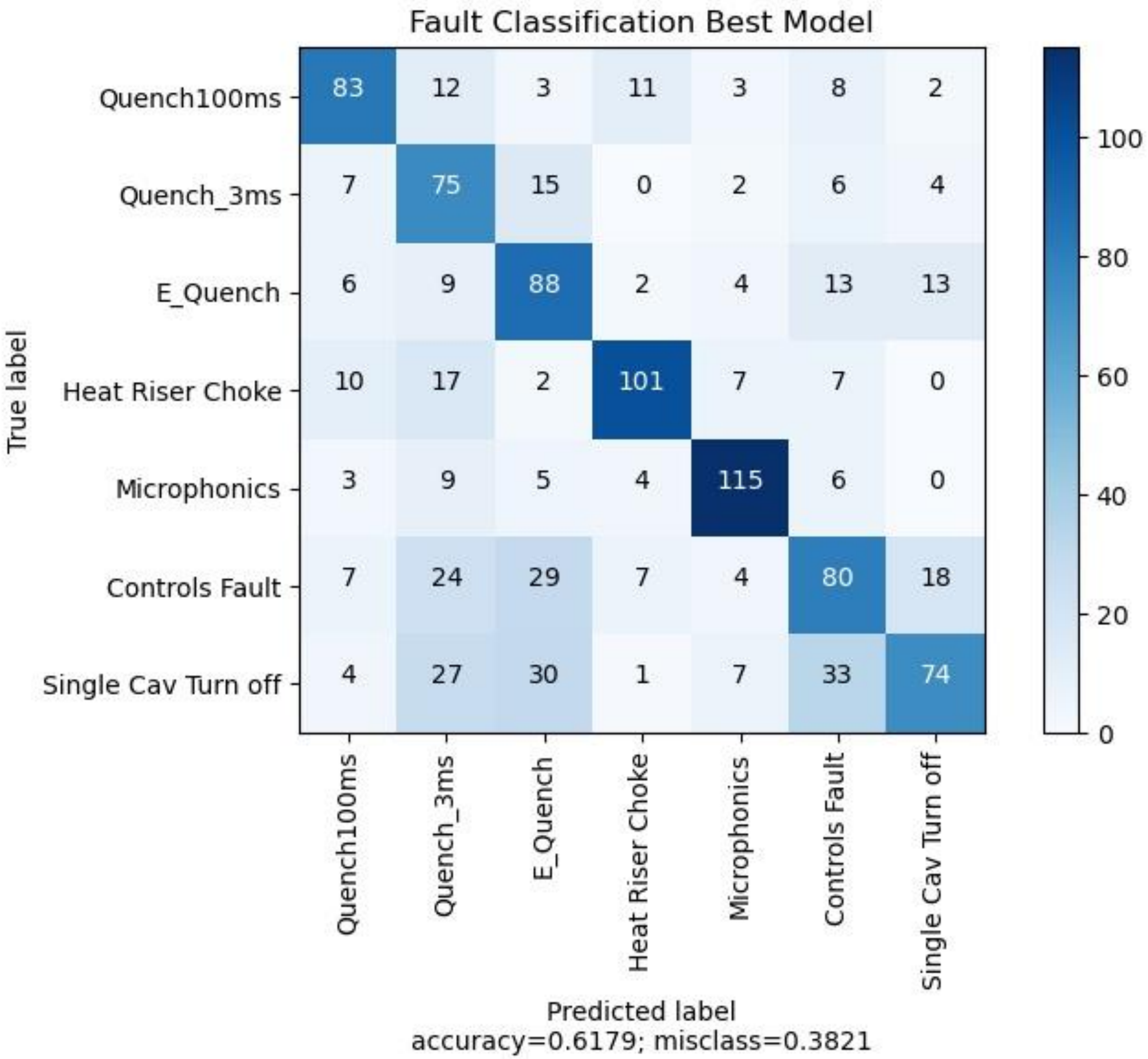
Model B: Fault Classifier

50 ms prior to fault



Model B: Fault Classifier

100 ms prior to fault



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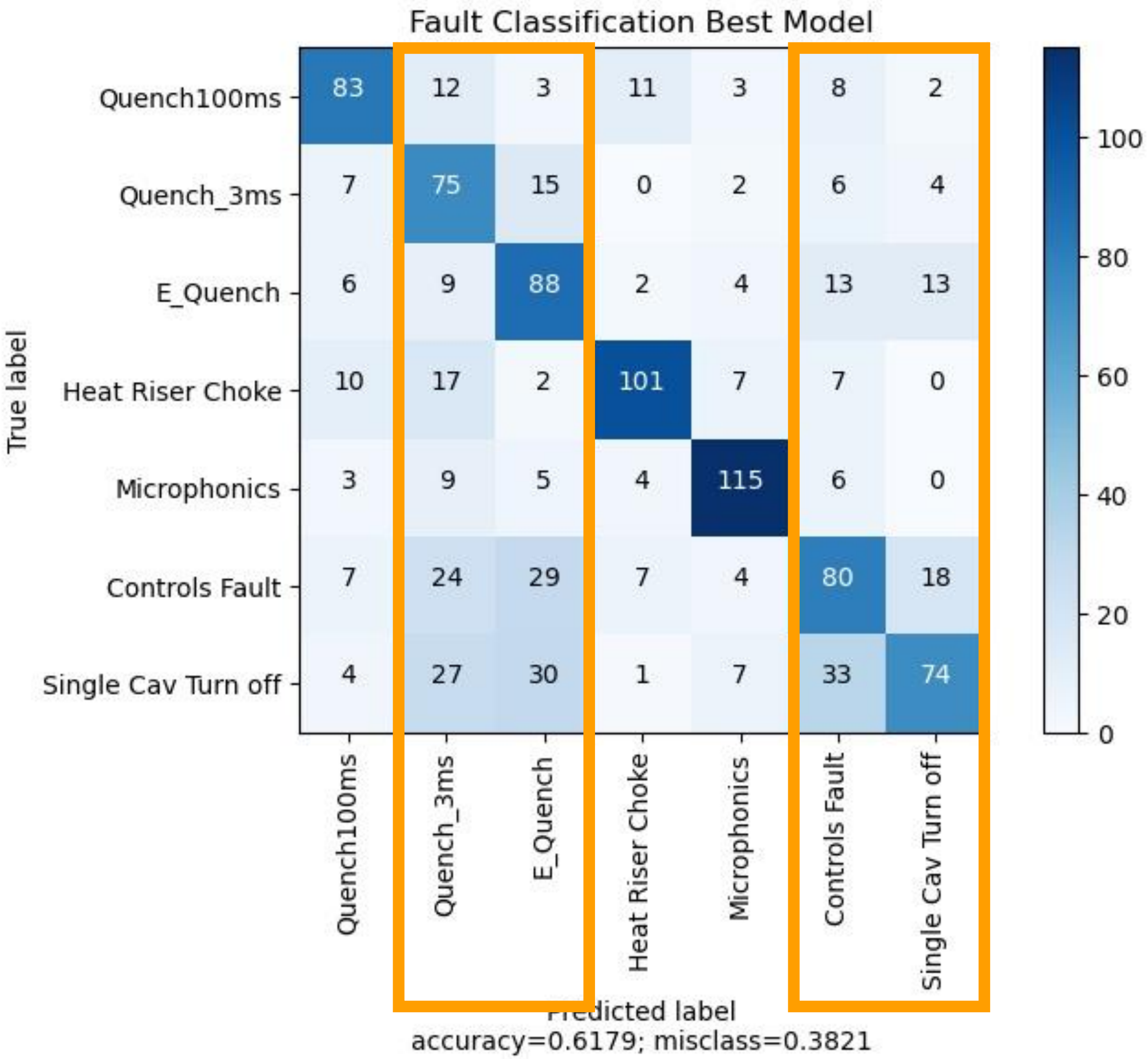

Model B: Fault Classifier

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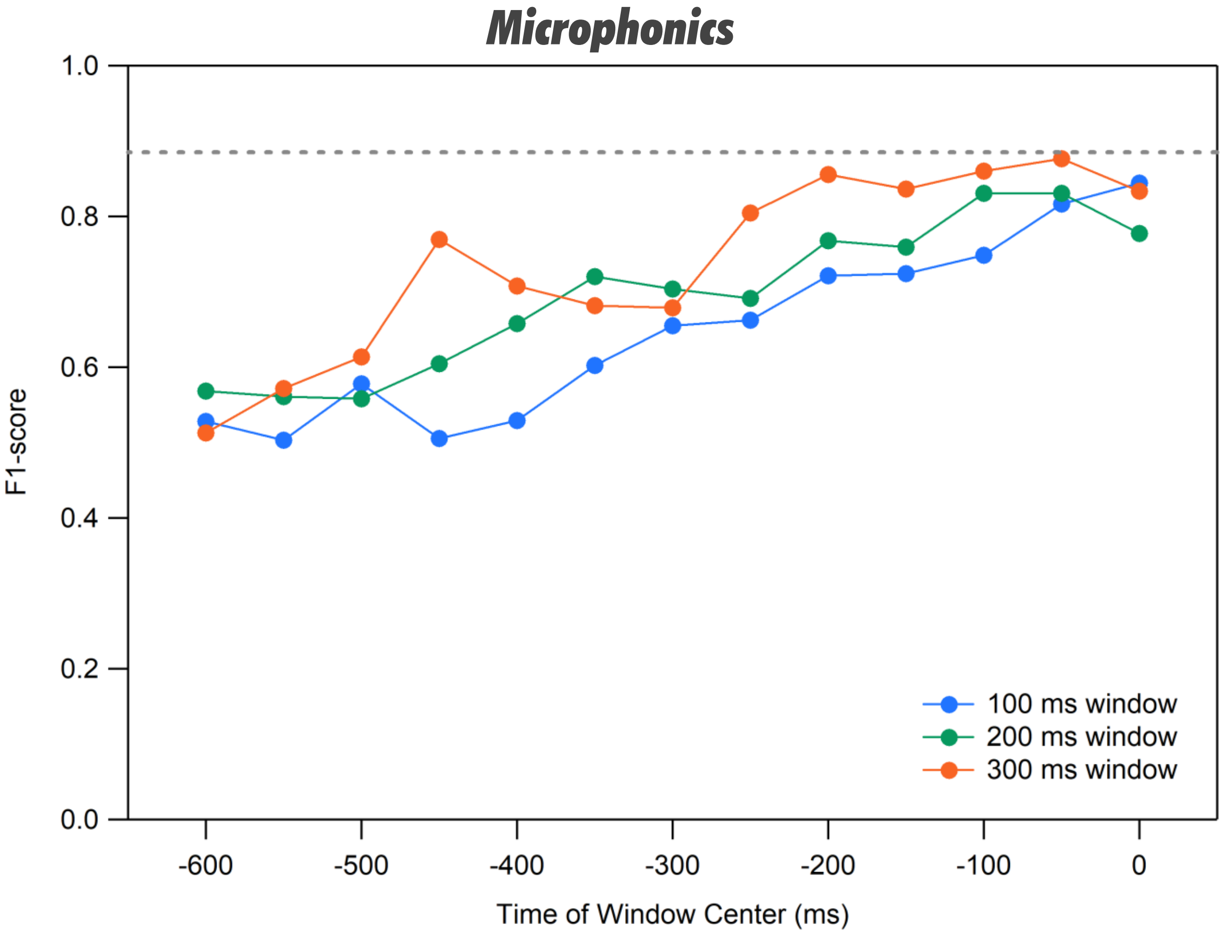

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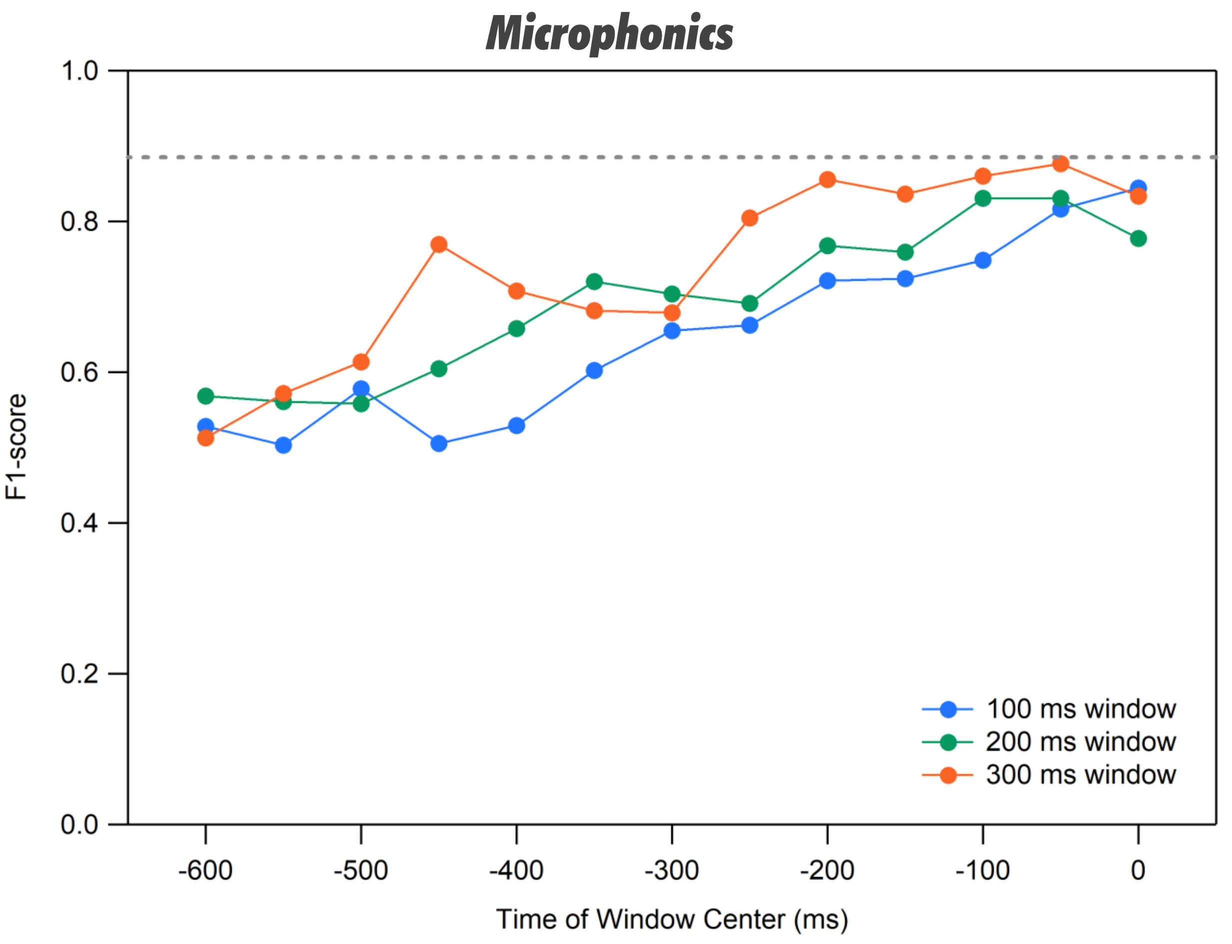

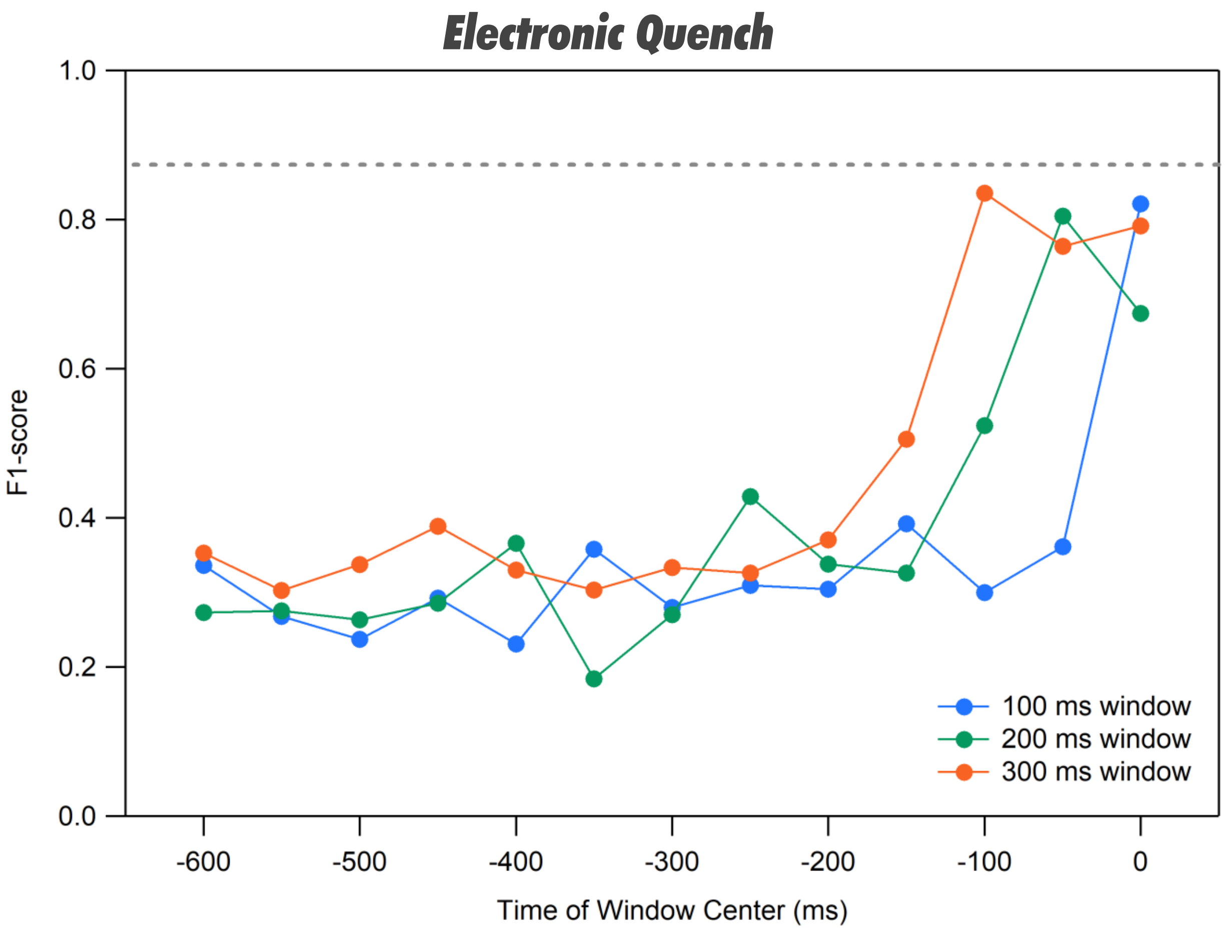

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Field Emission Management

Goal: maintain low levels of FE radiation without invasive interruptions to physics

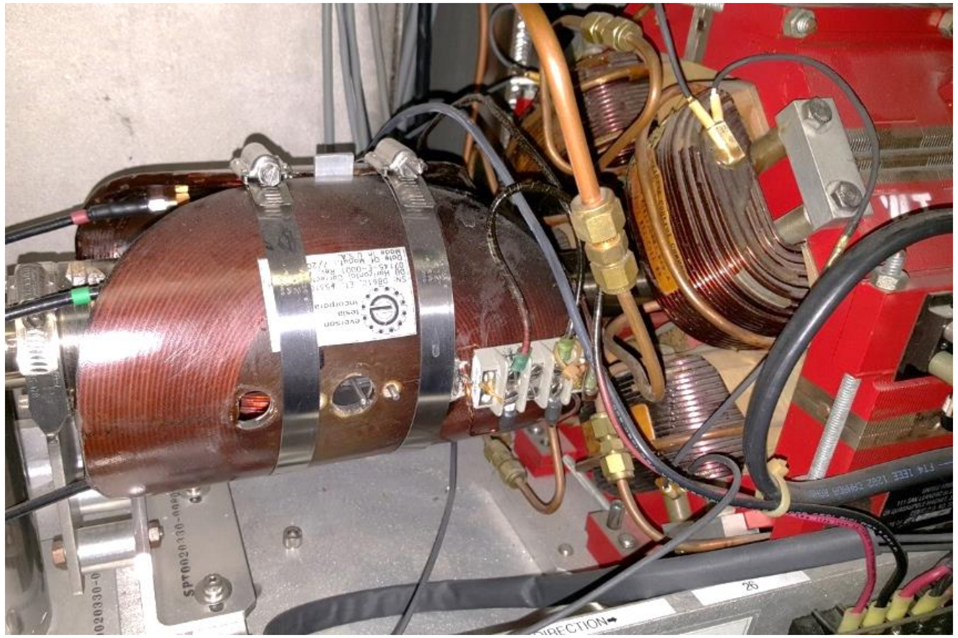
Description: use ML to model radiation levels and allow for off-line optimization of gradient distribution, identify cavities where FE onsets have changed

Solution: optimize surrogate model to minimize radiation via gradient reduction

radiation area

damaged beamline valve

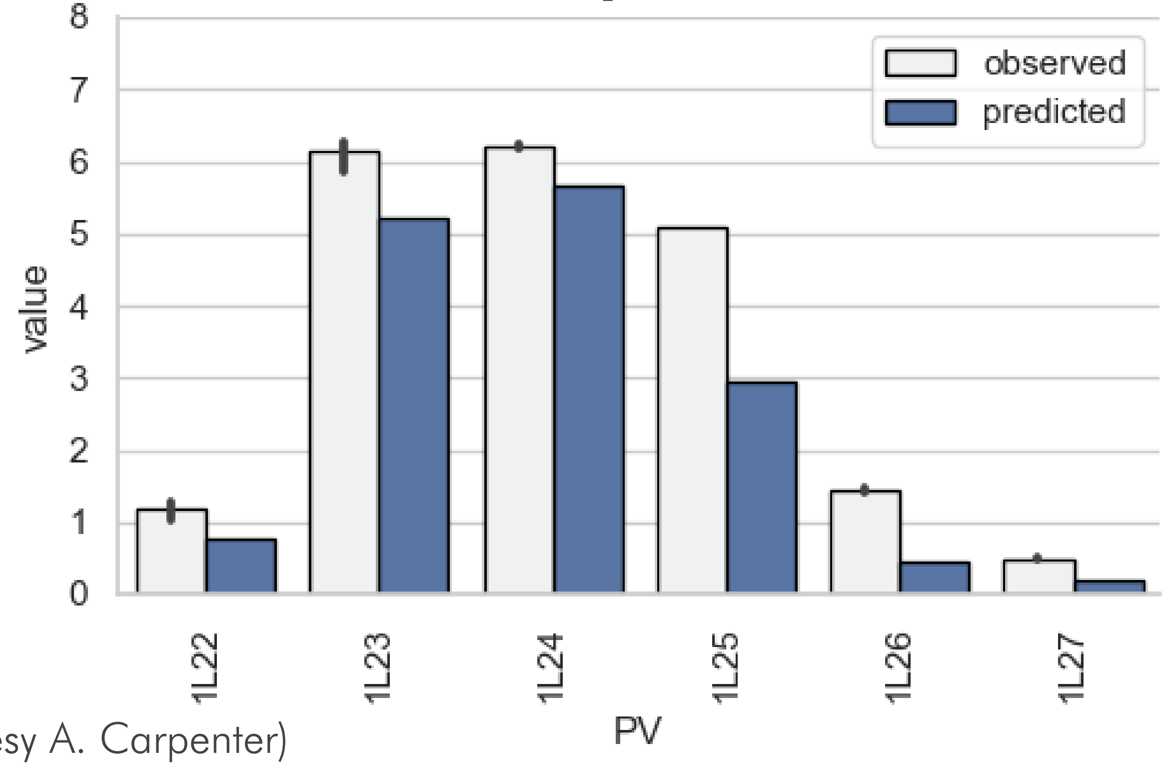
damaged magnet and cables



Field Emission Management: Proof-of-Concept Demonstration

1. set CEBAF to same gradient distribution as September 7 baseline
2. apply model-based optimized gradients to CEBAF

before optimization



after optimization

(courtesy A. Carpenter)

Field Emission Management: Proof-of-Concept Demonstration

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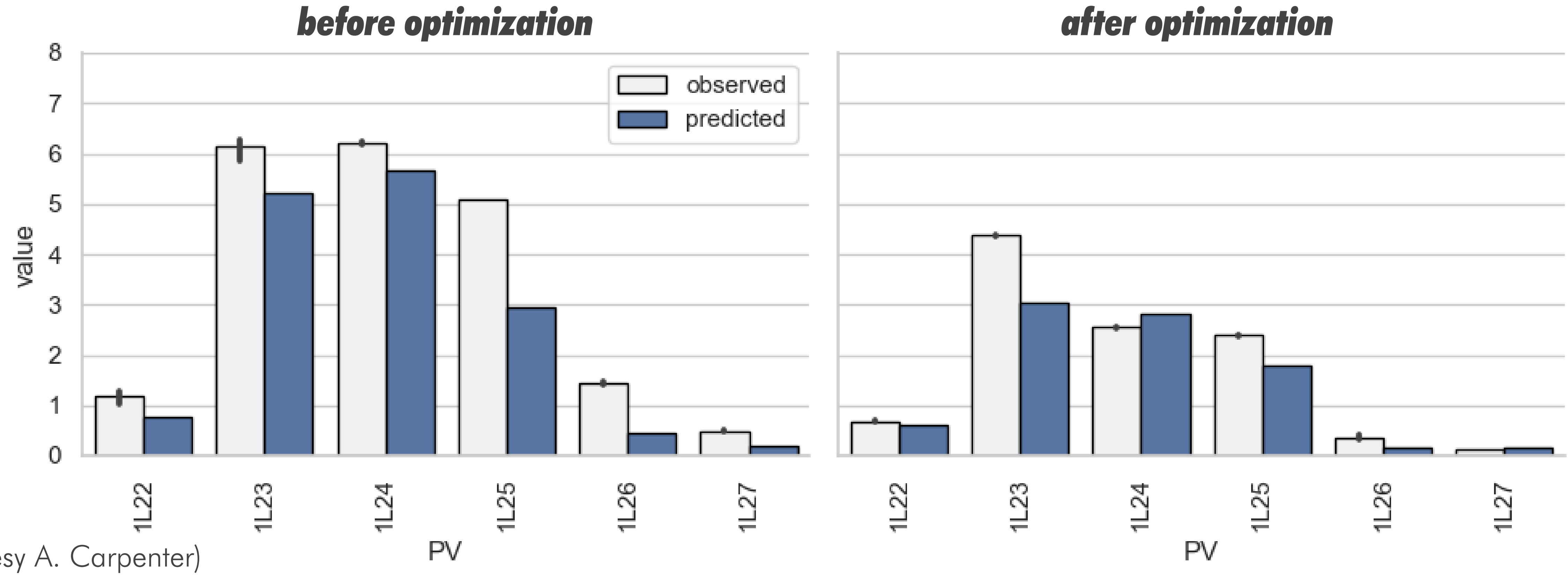
12 rem/hour decrease for 5 MV/m reduction in gradient



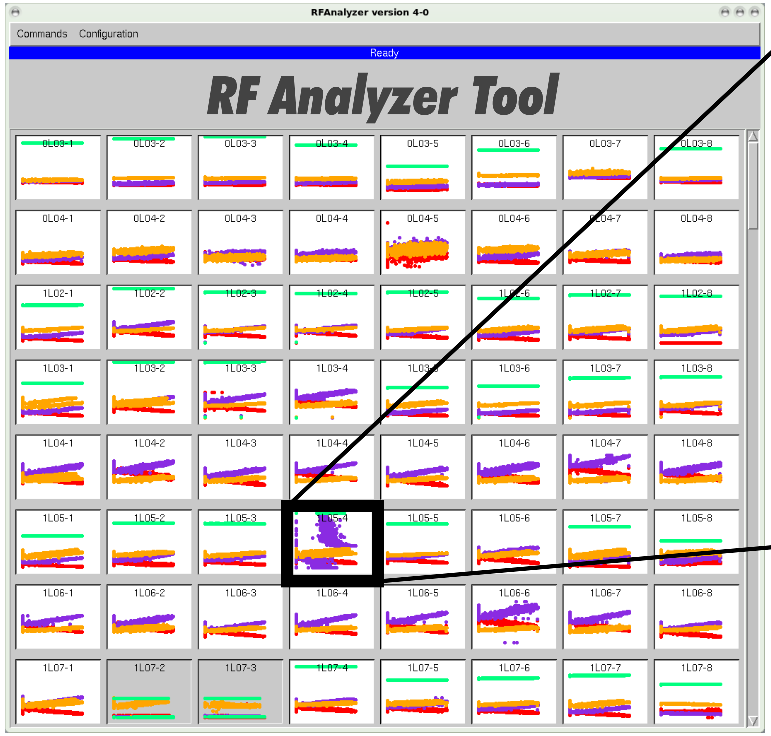
(courtesy A. Carpenter)

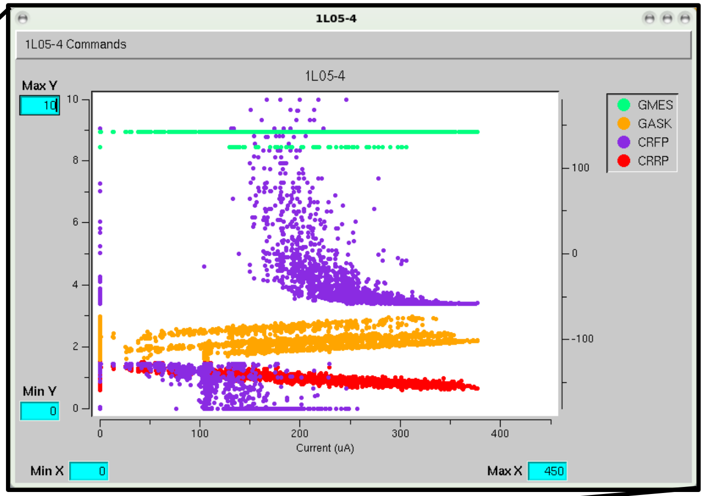
Cavity Instability Detection

Goal: improve beam availability by automating process of identifying unstable RF cavities

Description: SRF cavities can become unstable without presenting faults, identifying these unstable cavities with present diagnostics is difficult and time-consuming

Solution: (1) develop and install a new fast DAQ system for the legacy SRF cavities, and (2) apply ML to identify unstable cavities





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Importance of Having the Right Data

- accelerators produce a lot of data
  - ✓ CEBAF continuously archives 300,000+ signals
- however, it's not all useful for ML applications
- ML projects at JLab only possible because of newly available data

*P. Degtiarenko, US Patent 10,281,600

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C100 cavity fault classification → digital LLRF + waveform harvester

C100 cavity fault prediction → digital LLRF + streaming data

field emission management → NDX detectors*

cavity instability detection → fast DAQ

- data reliability is critical!

*P. Degtiarenko, US Patent 10,281,600

Summary

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  - ✓ for systems in place: maintaining reliability of data is a challenge
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  - ✓ for systems in place: maintaining reliability of data is a challenge
  - ✓ for systems in production: challenges with supply chain issues
- getting buy-in from all groups involved is still a challenge

Thank You.

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Mobile Diagnostic for Accelerator Operations

- ***Goal:*** develop a remotely controlled, semi-autonomous, mobile diagnostic that can be integrated into accelerator operations
- the mobile diagnostic system would provide potential benefit by:
  - ✓ ***reducing accelerator downtime*** by enabling remote inspection of beamline components and reducing the need for short, controlled accesses to the accelerator tunnel, and reducing the time required to perform standard radiation surveys
  - ✓ ***reducing machine tuning-time*** by acquiring dynamic measurements, e.g. beam loss and radiation measurements, under operational conditions at arbitrary locations along the beamline