Field Emission Mitigation in CEBAF SRF Cavities Using Deep Learning

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Abstract

The Continuous Electron Beam Accelerator Facility (CEBAF) at Jefferson Lab operates hundreds of superconducting radio frequency (SRF) cavities in its two main linear accelerators. Field emission can occur when the cavities are set to high operating RF gradients and is an ongoing operational challenge. This is especially true in higher gradient SRF cavities. Field emission results in damage to accelerator hardware, generates high levels of neutron and gamma radiation, and has deleterious effects on CEBAF operations. Therefore, field emission reduction is imperative for the reliable, high gradient operation of CEBAF that is required by experimenters. In this poster, we explore the use of deep learning architectures via multilayer perceptron and the use of tree based models to simultaneously model radiation measurements at multiple detectors in response to arbitrary gradient distributions. These models are trained on collected data and could be used to minimize the radiation production through gradient redistribution. This work builds on previous efforts in developing machine learning (ML) models, and is able to produce similar model performance as our previous ML model without requiring knowledge of the field emission onset for each cavity.

Introduction and Motivation

- CEBAF is a high energy, recirculating continuous wave linear accelerator utilizing 418 SRF cavities to accelerate electrons up to 12 GeV through 5-passes [1]
- Each SRF cavity has a unique gradient (MV/m) threshold over which field electrons are emitted

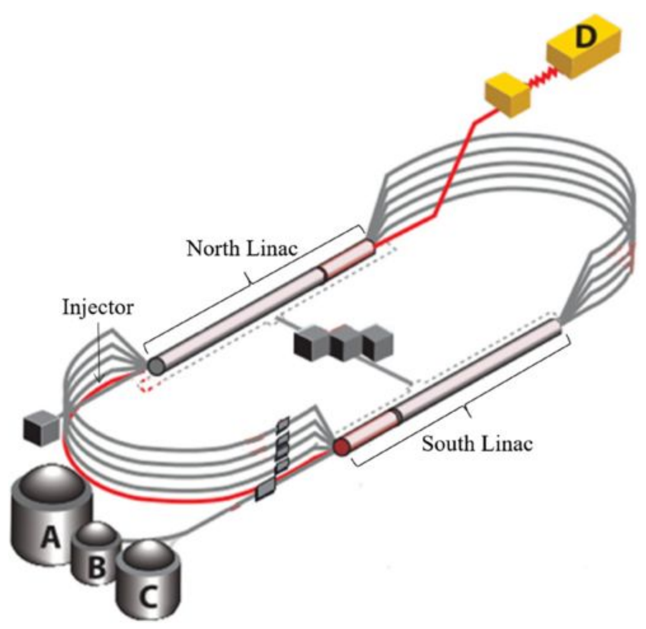

Fig. 1 Schematic of CEBAF

Fig. 2 Example of damage and radiation hazards due to field emission

- When field emitted electrons are accelerated and collide with another material, radiation (gamma and neutron) production occurs.
- This radiation damages the CEBAF's equipment
- The motivation is to explore an effective machine learning model for modeling radiation measurements so that the radiation can be minimized

Materials and Method

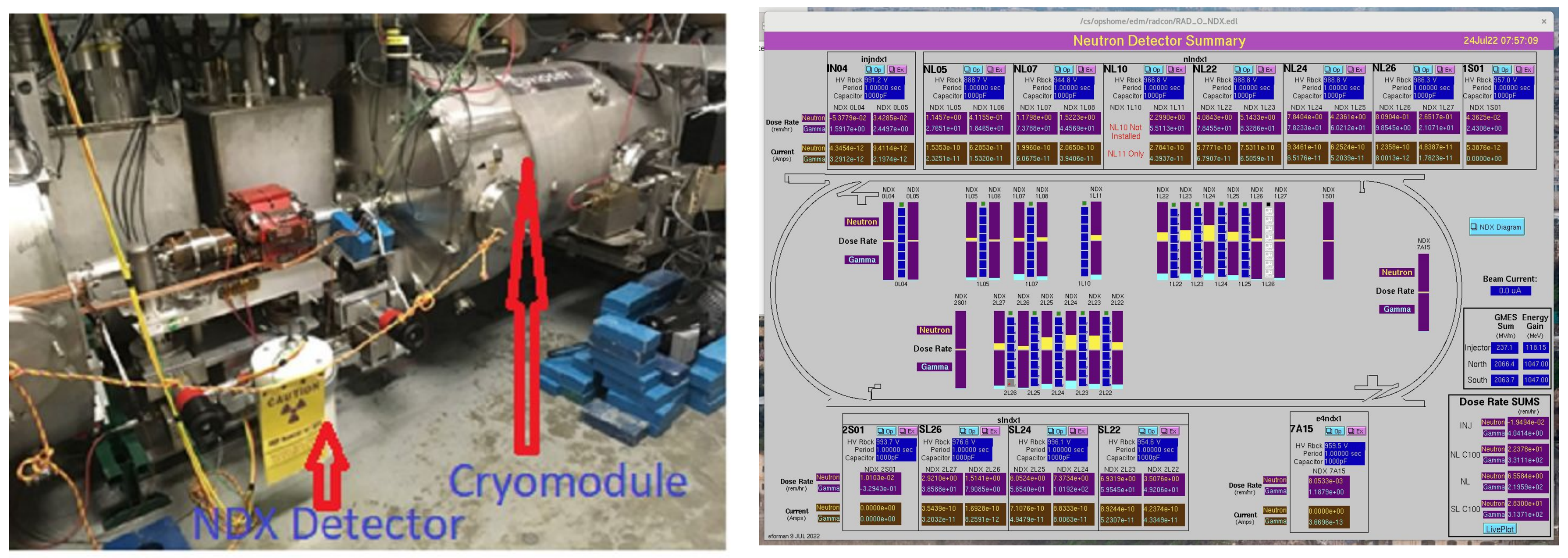

Fig. 3 Data collection and experimental set up

- Collected time series data for gradient, gamma and neutron measurements (Fig. 4)
- Data preprocessing and model learning (Fig. 5)

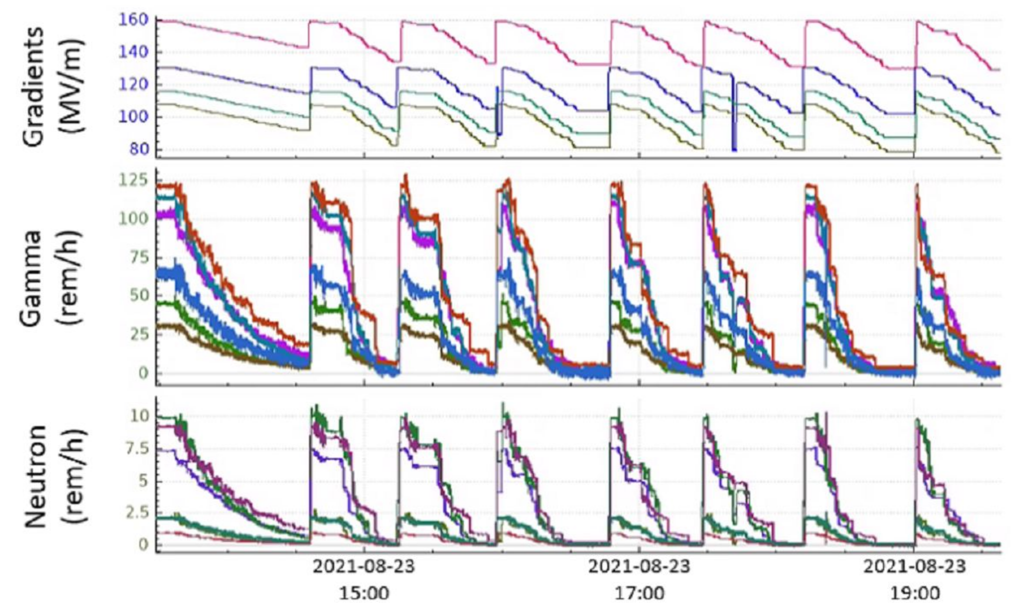

Fig. 4 Gradient, gamma and neutron measurement

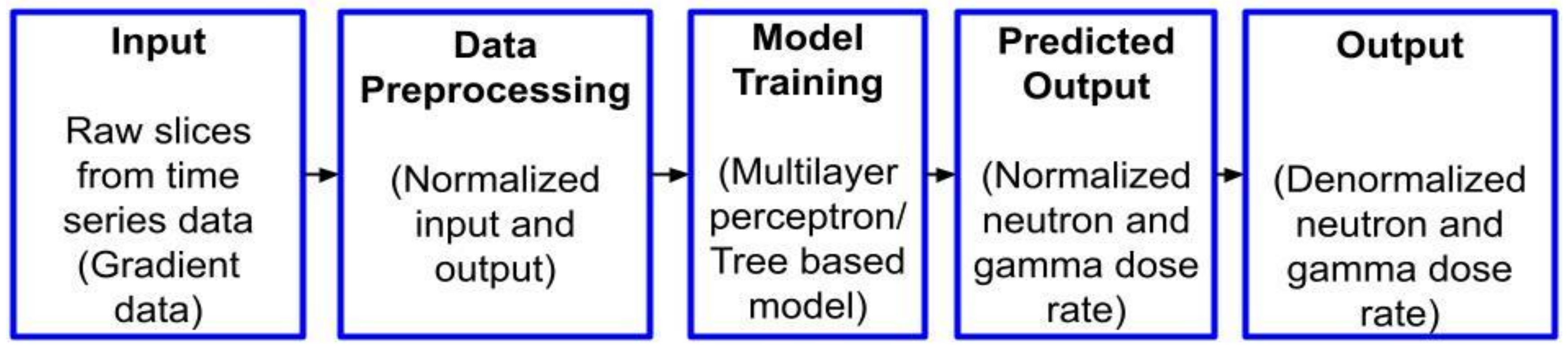

Fig. 5 Data preprocessing and model development

- MLP (Fig. 6) , XGBoost (open source software library) models are employed for modeling radiation
- Hyperparameters (optimizer=Stochastic Gradient Descent, learning rate=0.01, momentum=0.9) of MLP
- Hyperparameters (n_estimators=100, max_depth=6, max_leaves=0, min_child_weight=1, learning rate=0.2) of XGBoost

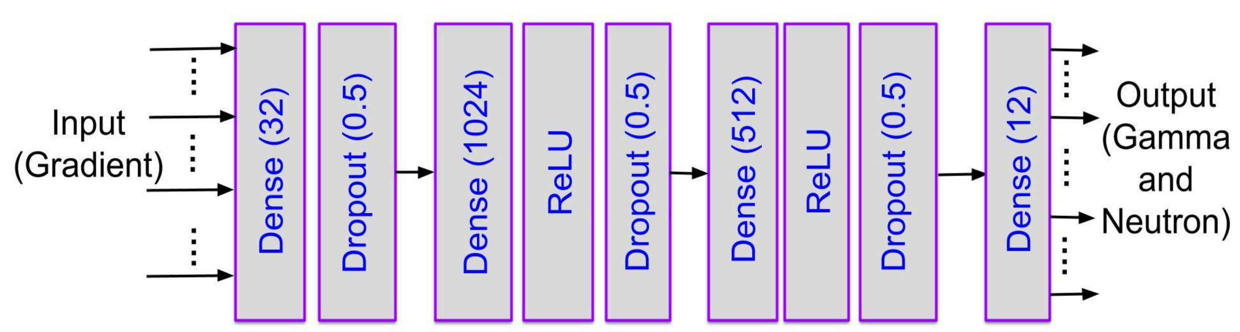

Fig. 6 : A baseline multilayer perceptron architecture with two hidden layers. Note: both inputs and outputs are individually normalized

Results

Table 1: Training, validation and test results of MLP and XGBoost model

Model	Metrics	Training	Validation	Test
MLP	R^2	0.989	0.986	0.985
	MSE	2.806	4.005	4.148
	MAE	0.853	1.015	0.985
XGBoost	R^2	0.998	0.986	0.986
	MSE	0.383	2.911	2.622
	MAE	0.345	0.853	0.794

R^2=Coefficient of determination, MSE= Mean squared error, MAE=Mean absolute error

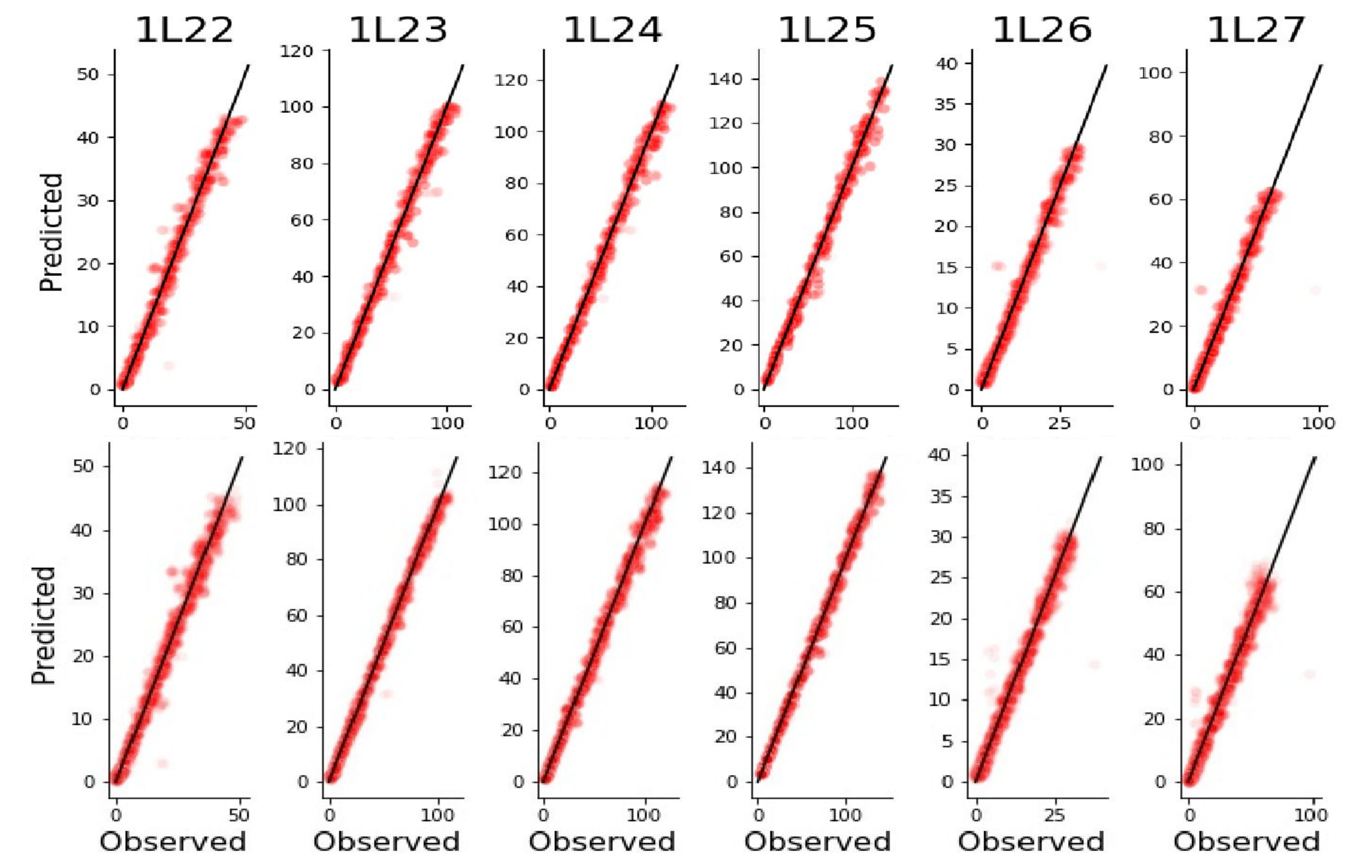

Fig. 7 Observed vs predicted plots for gamma radiation (rem/h) by the MLP (top) and XGBoost (bottom) models for test dataset at different detector regions (1L22-1L27)

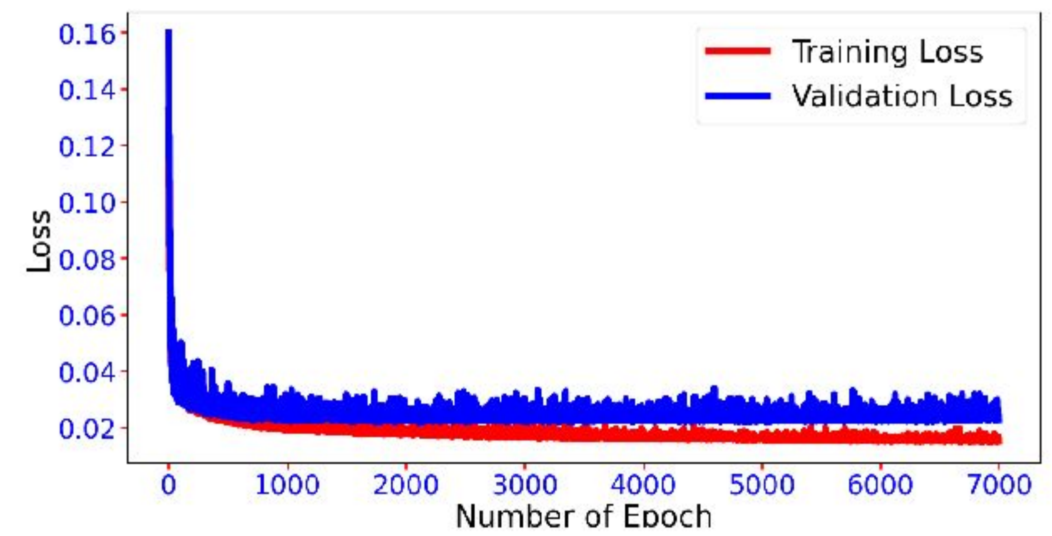

Fig. 8 Training and Validation loss for MLP model

Conclusion

- Demonstrated ability to accurately predict radiation measurements based solely on cavity gradients through both MLP and XGBoost models

Future Work

- Further work is required in order to keep these models performing well during the length of a run spanning few months in the face of changing CEBAF operational conditions

References

[1] Spata, Michael F. "12 GeV CEBAF Initial Operational Experience and Challenges." Proceedings of the 2018 International Particle Accelerator Conference, Vancouver, Canada, pp. 1771-1775 (2018).

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