A Data-Driven Anomaly Detection on SRF Cavities at the European XFEL

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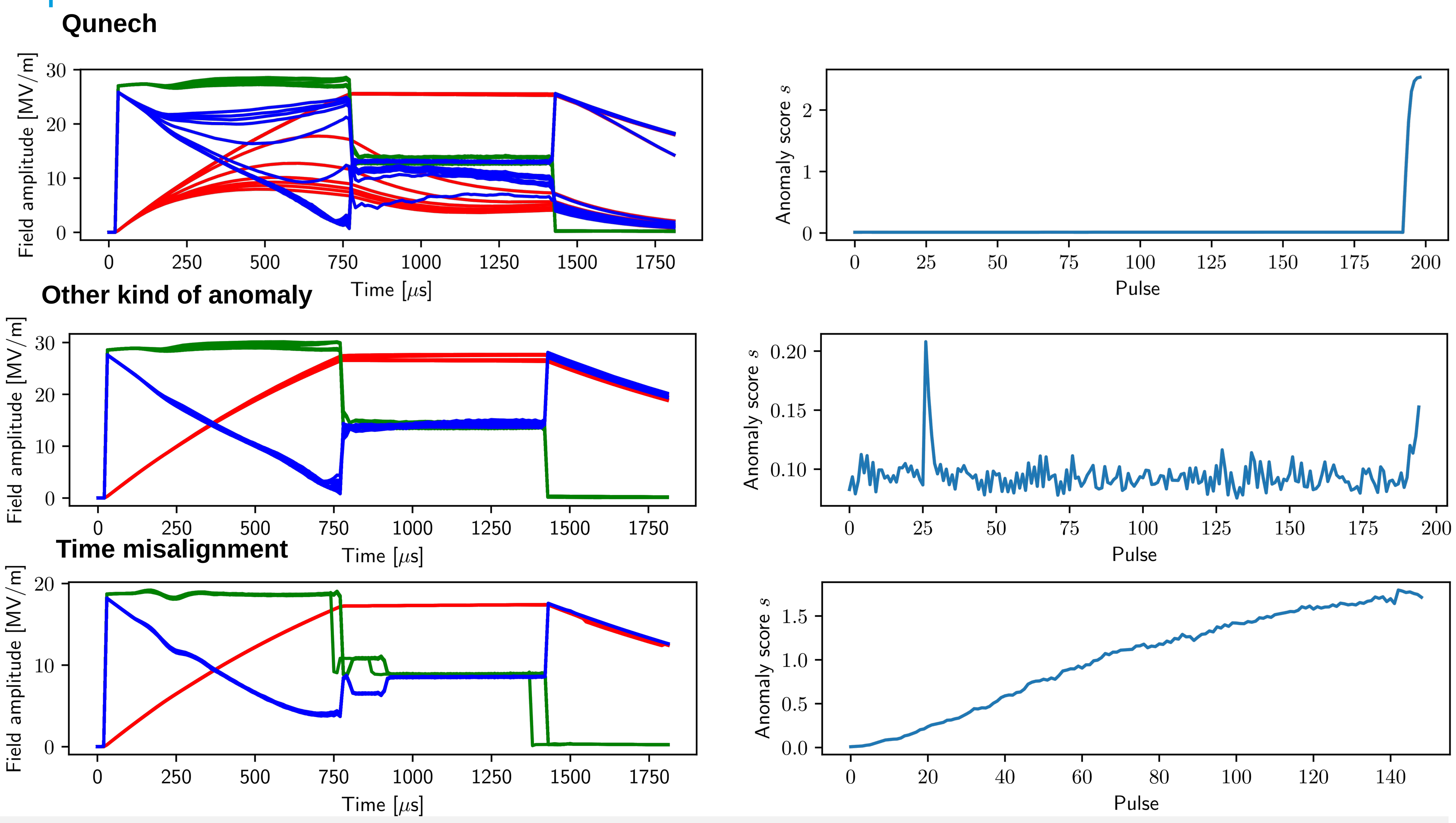
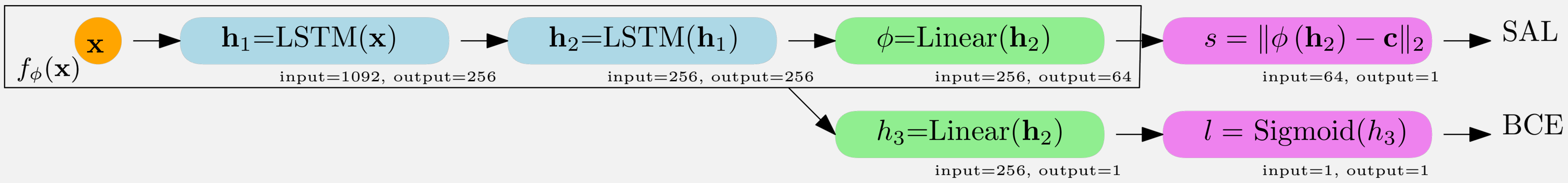
Abstract

The European XFEL is currently operating with hundreds of superconducting radio frequency cavities. To be able to minimize the downtimes, prevention of failures on the SRF cavities is crucial. In this paper, we propose an anomaly detection approach based on a neural network model to predict occurrences of breakdowns on the SRF cavities based on a model trained on historical data. We used our existing anomaly detection infrastructure to get a subset of the stored data labeled as faulty. We experimented with different training losses to maximally profit from the available data and trained a recurrent neural network that can predict a failure from a series of pulses. The proposed model is using a tailored architecture with recurrent neural units and takes into account the sequential nature of the problem which can generalize and predict a variety of failures that we have been experiencing in operation.

Inputs



Method



The model consists of **stacked Long Short-Term Memory** (LSTM) units with a **linear unit**,
The first LSTM layer encodes the input **x** into 256-dimensional vector **h1** , which is further passed another LSTM layer **h2** with identical dimensionality as h1

Semi-Supervised anomaly loss (SAL)

Values from **h2** are presented into the final linear layer that produces a 64-dimensional vector **φ**. We refer to transformed inputs into the final linear layer as features **f(x)**

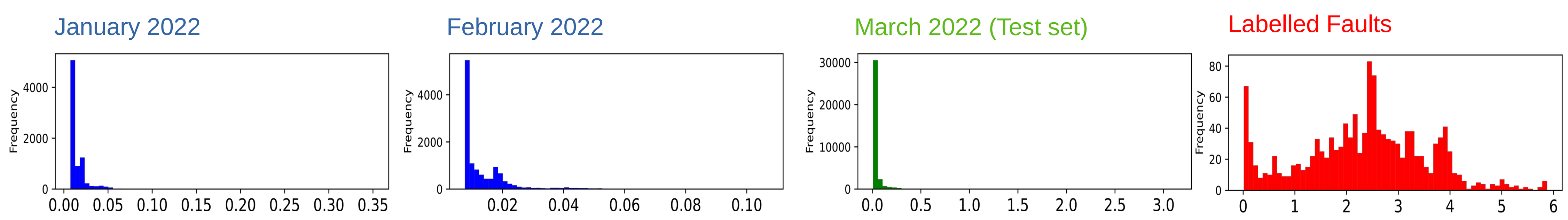
$$L(\theta) = \frac{1}{N}\sum_{i}^{N} \|f_\theta(\mathbf{x}_i) - \mathbf{c}\|_2 + \eta\|f_\theta(\mathbf{x}_i) - \mathbf{c}\|_2^{y_i}.$$

Binary cross-entropy loss (BCE).

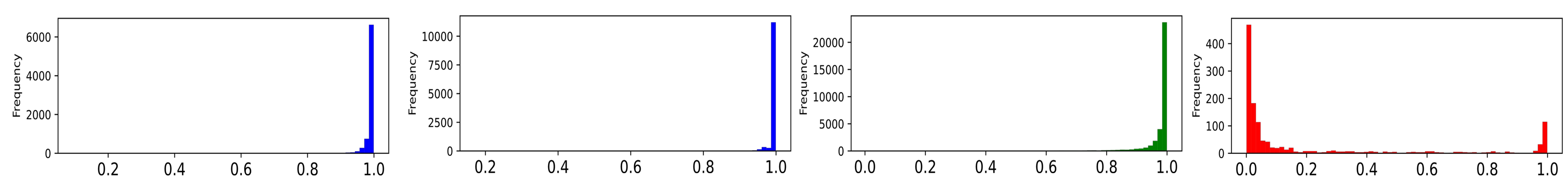
Unlike the model trained with SAL, the classifier trained with BCE has a **single binary value that signifies if the output is faulty or not**, therefore the last vector **h2** is fed into a linear unit with just one output **h3**

Results

SAL, histograms of anomaly scores *s*

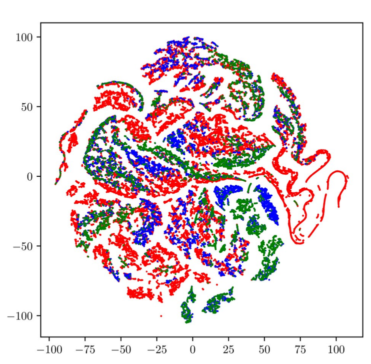


BCE, histograms of likelihood of healthly data *l*

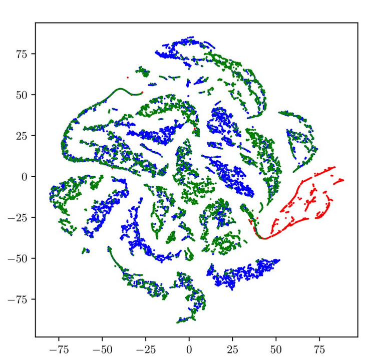


	Test set				March 2022	
Method	**TP**	**TN**	**FP**	**FN**	**TN**	**FP**
SAL	**103**	**7691**	**0**	**9**	**35034**	**952**
BCE	96	7685	6	16	34869	1117

TSNE embedding
Jan 2022,
Feb 2022,
Mar 2022 (test set)



TSNE embedding
Jan 2022,
Feb 2022,
Labelled (faulty)



Conclusion

- A data-driven and model-free approach to detecting **cavity anomalies**.
- Training model can bypass the **disproportionally many healthy training** samples by using a SAL
- The SAL allowed us to train the proposed model with an abundance of healthy data.
- The model is trained to project inputs to a **feature space** that reveals the potential for further classification of different types of faults.
- **Experiments** show that our method can identify a large part of faults in our test set.
- One of the **major limitations** is that waveforms may **vary over longer** periods.
- **In the future**, lower-dimensional features of the SAL model still carry the information about a fault, we would like to experiment with different models to achieve better **interpretability**.

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