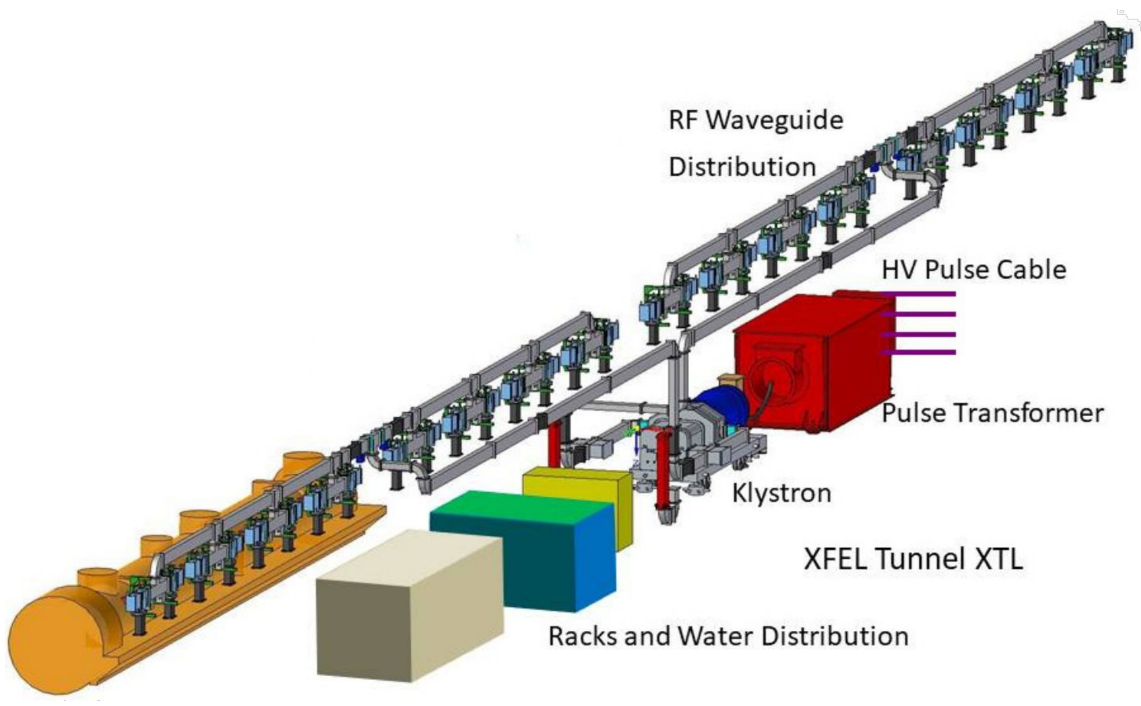

Source [2]

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Automated Anomaly Detection on European XFEL Klystrons

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High-power multi-beam klystrons represent a key component to amplify RF to generate the accelerating field of the radio frequency superconducting (SRF) cavities at European XFEL. Exchanging these high-power components takes time and effort, thus it is necessary to minimize maintenance and downtime and at the same time maximize the device's operation. In an attempt to explore the behavior of klystrons using machine learning, we completed a series of experiments on our klystrons to determine various operational modes and conduct feature extraction and dimensionality reduction to extract the most valuable information about a normal operation. To analyze recorded data we used state-of-the-art data-driven learning techniques and recognized the most promising components that might help us better understand klystron operational states and identify early on possible faults or anomalies.

MOTIVATION

- Klystrons are critical components for amplifying the RF power needed to accelerate particle beams at the European XFEL facility. Failure or suboptimal performance of klystrons can lead to beam disruptions and downtime.
- Klystrons are complex devices and diagnosing or predicting potential failures in them is challenging because they operate largely as "black boxes" from a signal viewpoint.
- The paper aims to leverage machine learning techniques, specifically unsupervised anomaly detection, to better understand the operational states of klystrons and identify potential faults or anomalies before they lead to failures and downtime.
- By training models on normal klystron signal data, the authors seek to detect deviations from normal behavior that could indicate incipient issues, providing early warning to take preventive action and maximize klystron uptime.

METHODS

The paper uses an unsupervised deep one-class classification approach [1] with an LSTM neural network model. The core idea is to train the model solely on normal klystron signal data, so that it learns to characterize normal behavior patterns. Any significant deviations from these learned patterns are then flagged as anomalies.

The anomaly score is calculated using the "one-class loss" function, given by the equation:

$$\arg\min_\theta \underbrace{\| f_\theta(\mathbf{x}) - \mathbf{c} \|_2}_{\text{anomaly score } s(\mathbf{x})}$$

Where:

- *f* is the neural network function with parameters θ
- **x** is the input data sample
- **c** is a fixed, randomly chosen hypersphere center vector in the output space R^M
- The objective is to minimize the distance between the network's output *f*_θ(**x**) and the center **c** for normal data samples

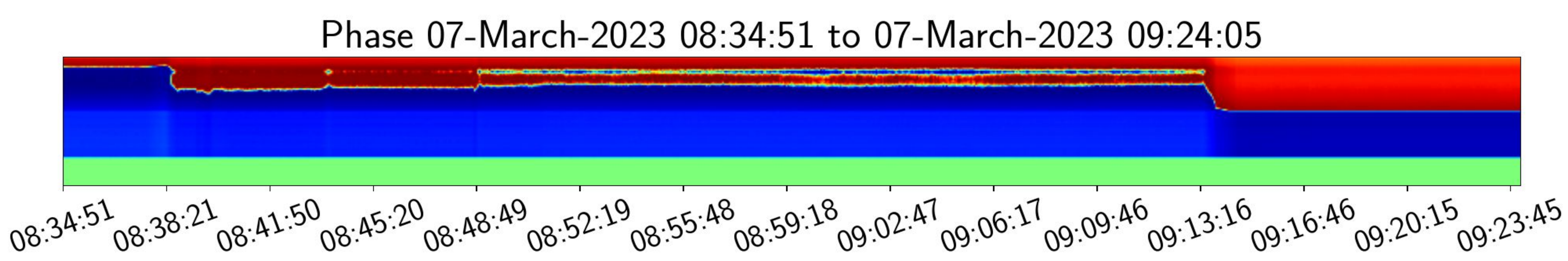
RESULTS

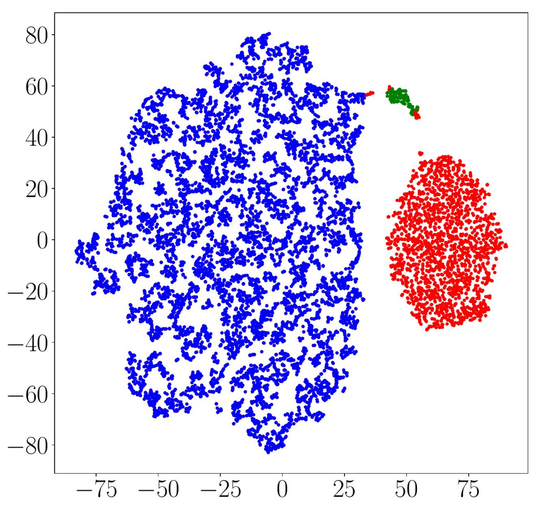
Event on March 7, 2023:

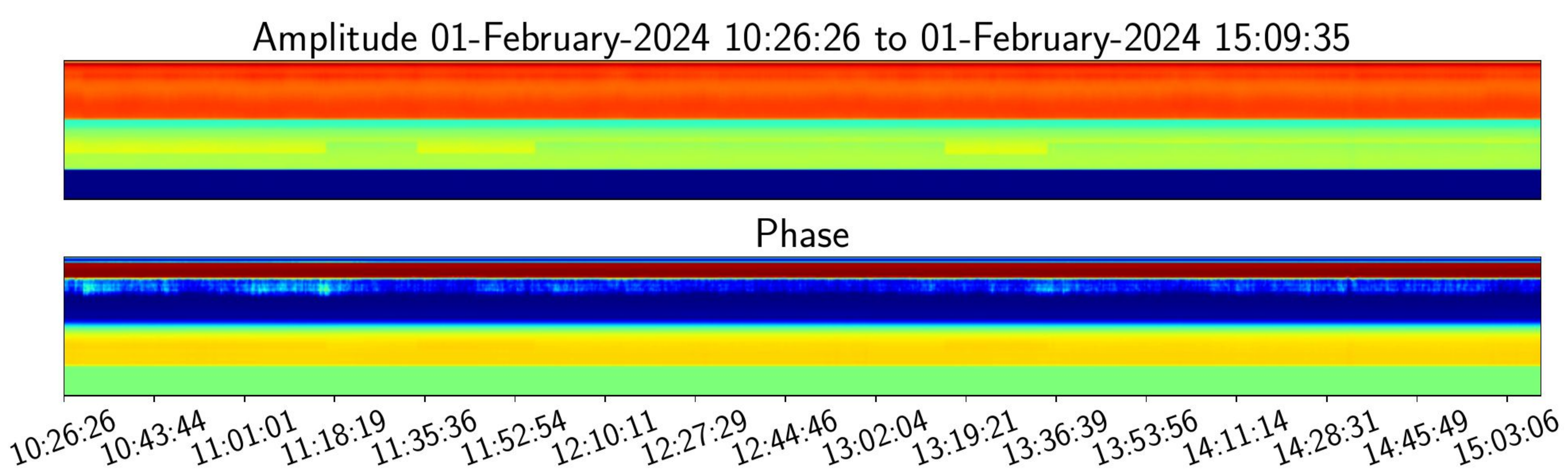
- Suspected case of multipacting (resonant electron trajectories) in klystron A13
- The anomaly score started showing a noticeable increase around 9:13am, well before the event escalated
- This early detection could have alerted operators to the developing multipacting issue

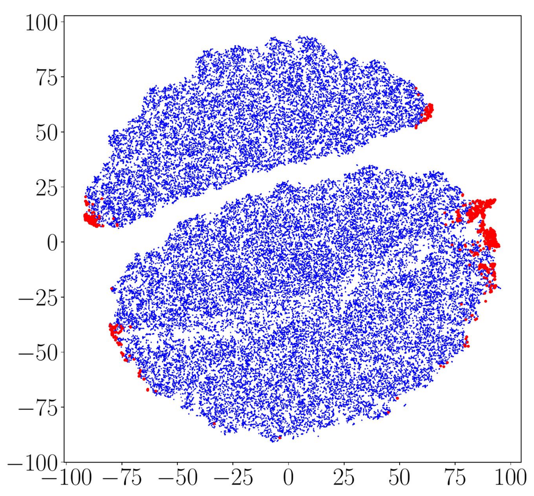
Event on February 1, 2024:

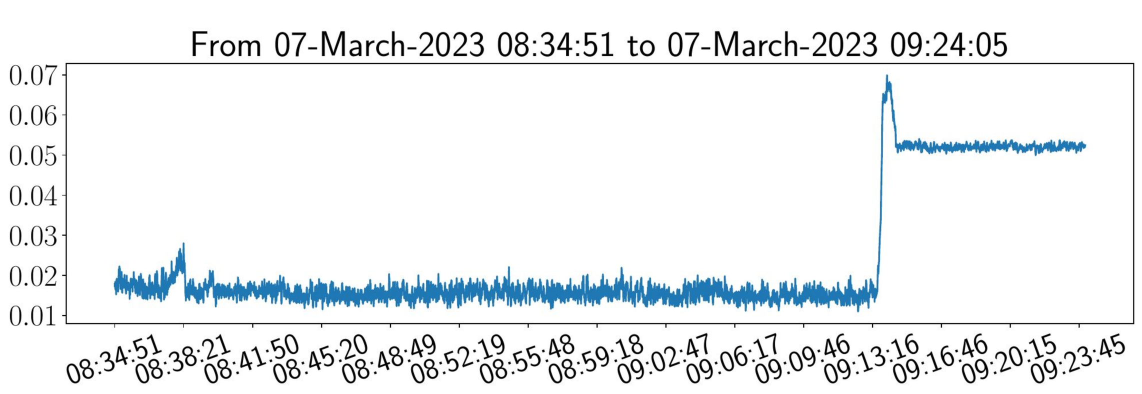
- Catastrophic failure of klystron A16 due to likely excessive dark current
- Anomaly scores showed mild fluctuations over an extended period (10:30am - 3pm) before complete failure
- A noticeable peak around 2:30pm preceded severe signal disruption
- Significant fluctuations were also visible in the input phase waveforms during this period

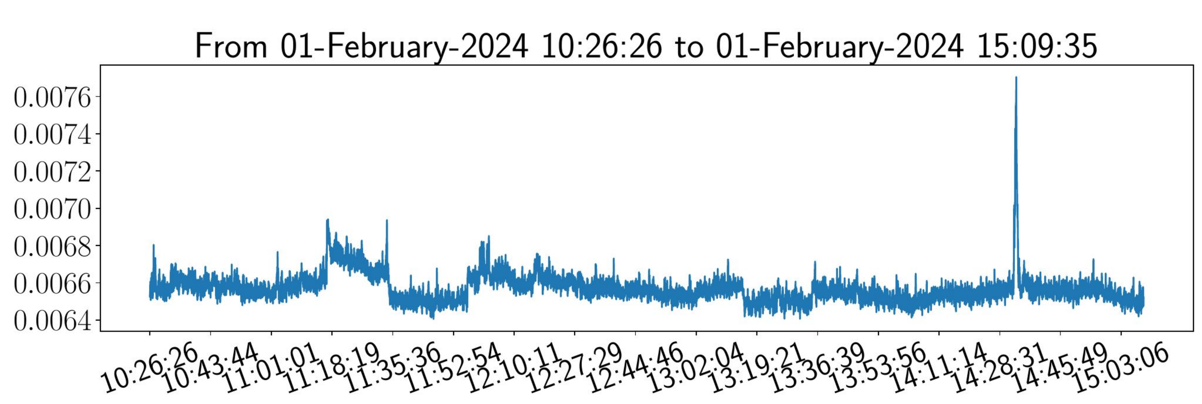












CONCLUSION

In this work, we demonstrated the application of unsupervised deep one-class classification with an LSTM model for sequential anomaly detection in the operational signals of high-power klystrons at the European XFEL facility. By training solely on normal waveform data, the model learns to characterize standard klystron behavior and identify deviations as potential anomalies or faults.

We presented two case studies of actual events - a suspected multipacting issue on 7 Mar. 2023, and a catastrophic klystron failure on 1 Feb. 2024.

Our algorithm identified precursors, flagging anomalous waveform patterns before the issues escalated to system failures or downtime which were assessed by the experts.

[1] L. Ruff et al. , "Deep one-class classification," in Proceedings of the 35th International Conference on Machine Learning vol. 80, 2018, pp. 4393–4402. https://proceedings.mlr.press/v80/ruff18a.html
[2] Bousonville, M., et al. "European XFEL High-Power RF System–The first 4 years of Operation." *Proc. 12th Int. Particle Accelerator Conf.(IPAC'21)*. 2021.