Multivariate Time Series Prediction for Outage Prediction & Diagnosis

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Problem Statement

- **Fermilab Accelerator Complex**
  - United States' flagship facility for High Energy Physics (HEP).
  - For the linear accelerator (Linac) alone, the control system monitors and issues commands to 4000+ control system parameters at frequencies ranging from 15 Hz to once every few minutes.
- **Current Operations:**
  - Mostly Reactive: 15000+ daily alarms, along with additional status indicators.
  - On beam interruption, operators investigate through data the source of unplanned beam outage from the FNAL Main Control Room.
- **Challenges**
  - False alarms waste operators' time.
  - No predictive power to take preventive actions.
  - Number of devices and amount of data to monitor exceed human capacity to process.
  - Inconsistent and incorrect labeling complicates bookkeeping.

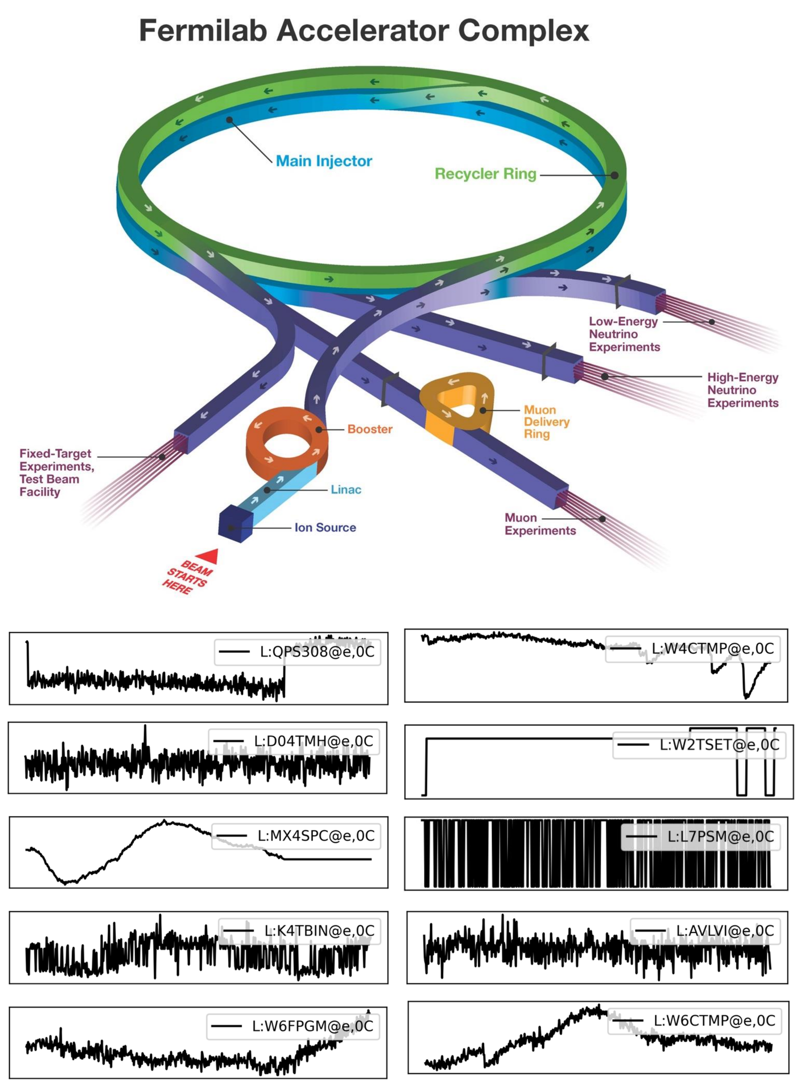

Figure 1: Fermilab accelerator complex with sample device data collected from Linac.

Objective

- Evaluate state-of-the-art deep learning techniques for multivariate time series analysis to automate outage detection, prediction, and labeling.

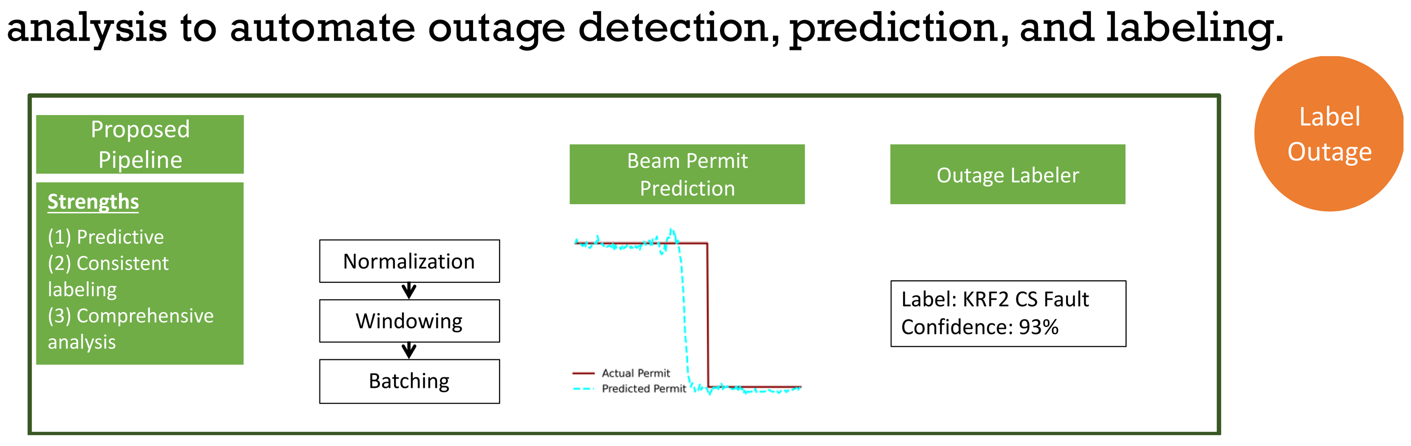

Figure 2: Overview diagram illustrating proposed predictive maintenance pipeline along with its potential benefits over current practices.

Data Collection and Preprocessing

- **Data Logger**
  - Accelerator control system's data logger nodes record data streams into circular buffers.
  - Pipeline created by the developers at the FNAL's Controls Department using SOTA tools & techniques.
  - Solves a common problem and is being used on other ML projects.
- **Data Stats**
  - L-CAPE makes requests over 2703 control system parameters and stores each request in Parquet format with the lossless snappy compression.
  - The 2703 devices include 1719 reading, 842 settings, and 142 status bits.

> **Finding-1:** Status bits show distinct patterns for different type of operator labeled outages, highlighting inconsistencies and ambiguity in human-generated labels

- **Operator-Labeled Outages**
  - Operators assign labels based on their findings and prior experience, generally only for outages lasting longer than one minute.
  - Our data contains 80 operator-labeled outages and 125 unlabeled outages.
  - For each outage, we save a window of 30 seconds before the outage starts and 10 seconds later. We skip outages of less than 10 seconds
- **Bit-Labeled Outages**
  - Status devices store multiple bits of information, where each bit is an indicator for a specific system event, including high voltage conditions or spark trips.

Experimental Setup

- **Beam Permit Prediction: Modeling Parameters**
  - Look-back window size: 30 ticks; Look-forward window size: 60 ticks; Gap: 30 ticks
  - Feature dimension: 1719 (only analog devices)
  - Training data: 40 operator-labeled outages, 75 unlabeled outages, and 375 non-outages.
  - Validation data: 10 unlabeled outages, and 21 non outage instances.
  - Test data: 40 operator-labeled outages, 40 unlabeled outages, and 31 non-outages.
- **Outage Labeler**
  - Look-back window size: 6 ticks; Feature dimension: 2703 (all devices)
  - The data for outage classification is limited to the 80 operator-labeled outage instances.
  - We used 8-fold cross-validation during hyperparameter tuning.

Evaluation

Table 1: Performance Comparison (80 outages and 31 non-outages)

	True Positives	Early Detected	Late Detected	Time Diff (in secs)	False Positives	#Params	Inf. Time (in secs)
LSTM	80	75	5	-11.16	9	181K	8.17
Transformer	79	72	7	-9.62	8	662K	1.77
N-BEATS	79	34	45	-2.67	4	496M	33.38
N-HiTS	79	71	8	-9.34	10	135M	17.39
TiDE	80	65	15	-8.50	10	642K	3.17
TSMixer	76	49	27	-5.40	8	320K	5.72

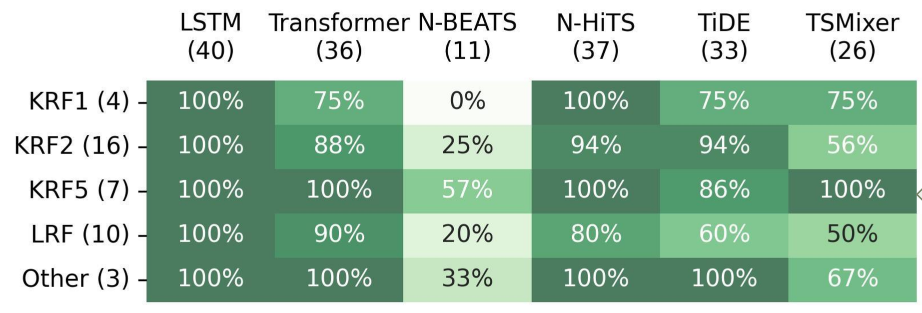

Figure 3: Model-wise detection rate by outage types.

> **Finding 2:** LSTM outperforming SOTA DL architectures on multiple performance criteria.

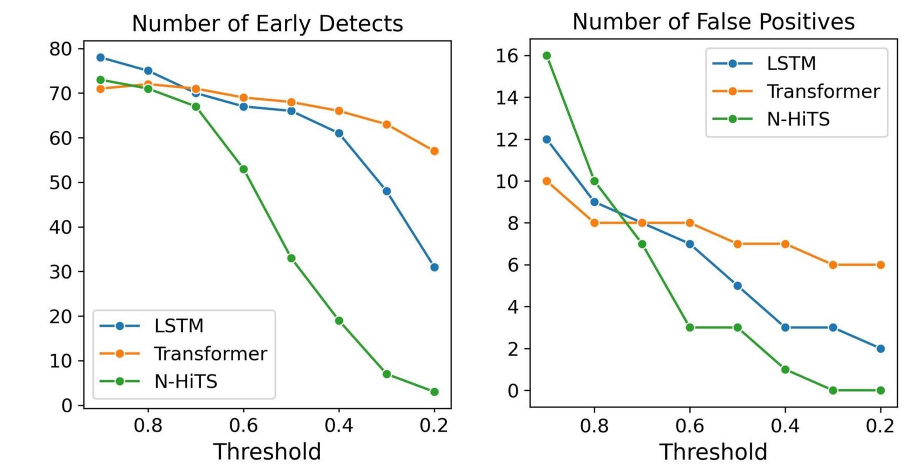

Figure 4: Sensitivity of the top three models to varying threshold values.

> **Finding 3:** Transformer and LSTM models exhibit greater robustness to threshold variations compared to N-HiTS.

- **Impact of look-back window size:**
  - While increasing the size of the look-back window led to a decline in LSTM and Transformer performance, most linear models (excluding TiDE) showed improvement.
- **Impact of gap:**
  - A gap between look-back and look-forward windows helps focus on future steps, but if too large, it weakens predictive power; if too small, it limits forecasting benefits.
  - We observed an improvement in the early detection rate for all models when the gap was increased to 60, and a decline in performance when the gap was reduced.
  - This suggests that 2–4 seconds before an outage, models detect precursor disturbances in correlated devices.

> **Finding 4:** High degree of consistency between the pattern-based random forest-labeler and the bit-labeler. The number of unlabeled outages reduced to 1 (from 130), and particularly very short outages can now be labeled.

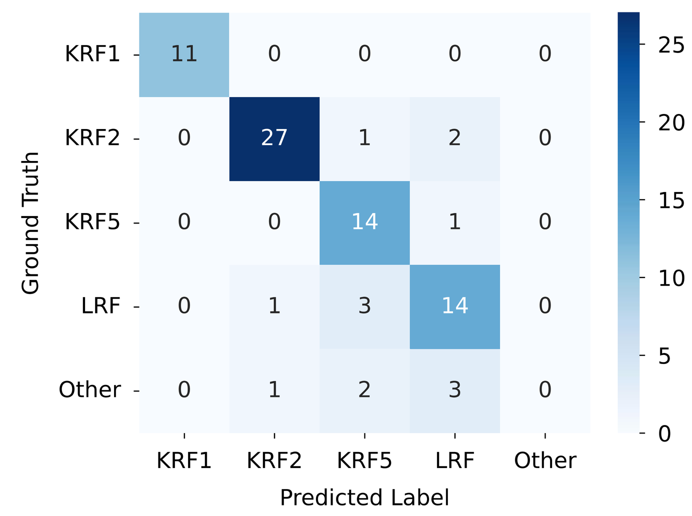

Figure 5: Random forest labeler performance on operator-labeled outages across fault types.

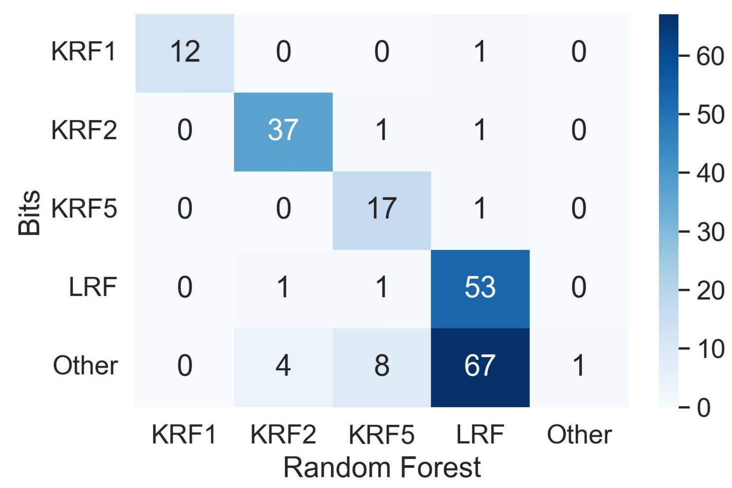

Figure 6: Performance comparison of random-forest labeler and bit-labeler for outages without human labels.

Discussion & Future Work

- **Finding 5 (Interpretability is important):** Operators are not only interested in predictions but also in the interpretability of the predictions (e.g., which devices at what time led to this outage?)
- **Finding 6 (Significance of batch normalization):** Batch normalization obscure long-term shifts and trends but helpful in identifying abrupt local changes.
- **Finding 7 (Data loading is time consuming):** Overlapping windows, ensuring correct order, and multiple permutations of feature space and look-back, look-forward windows restricts parallelism and increases computational load.

Acknowledgements

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