A Preliminary Study on Physics-Guided Deep Learning for Smart Battery Abuse Detection

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***Abstract*—Battery safety is a critical requirement for electric vehicles and energy storage systems, as lithium-ion battery failures can lead to severe hazards. However, existing research is limited by the scarcity of publicly available abuse datasets and the difficulty of collecting controllable fault data. This study aims to develop a lightweight baseline framework for binary battery safety classification using physics-guided synthetic data. Electro-thermal battery behavior is simulated using the Doyle-Fuller-Newman model under normal operation and two abuse scenarios. A BiLSTM network is trained to classify SAFE and DANGER states from multivariate time-series signals. Experimental results show strong detection performance with an accuracy above 94% and a ROC-AUC of 0.968. These findings demonstrate that physics-based synthetic data can effectively support data-driven battery safety monitoring and provide a foundation for more advanced early-warning systems.**

***Index Terms*—Battery safety, BiLSTM, Early warning, Horizon-based labeling, Lithium-ion batteries, Machine learning, Smart battery, Synthetic dataset, Thermal runaway, Time-series classification**

I. INTRODUCTION

The rapid adoption of lithium-ion batteries in electric vehicles and energy storage systems has intensified safety concerns. Catastrophic failures such as thermal runaway often occur abruptly, leaving minimal reaction time once conventional thresholds are exceeded. As a result, data-driven early-warning systems based on deep learning have gained attention for detecting subtle precursors to failure [1].

However, progress remains constrained by two major challenges. First, publicly available and well-labeled abuse datasets are scarce due to safety and cost limitations of experimental testing. Second, most existing models rely on fixed thresholds or implicit prediction horizons, limiting their ability to quantify time-to-failure [2].

Physics-based simulations offer a safe and controllable alternative for exploring hazardous scenarios. Although DFN electro-thermal models have been widely used to analyze battery behavior, their application has mostly focused on individual scenarios rather than large-scale dataset generation with explicit early-warning labels [3], [4].

This paper addresses these gaps by presenting a compact framework that integrates physics-guided data generation with horizon-based labeling and sequence learning. The main contributions are:

- A synthetic multi-scenario battery abuse dataset generated using DFN simulations.
- Horizon-based labeling for short-term danger prediction.
- A multi-task BiLSTM model for joint failure forecasting and abuse-mode classification.

II. SYSTEM DESIGN

A. Synthetic Data Generation

Battery behavior is simulated using the Doyle-Fuller-Newman (DFN) electro-thermal model implemented in PyBaMM. Three scenarios are considered:

- Normal cycling
- Overcharge abuse
- Thermal abuse

Randomized current rates and thermal parameters are applied to generate diverse operating conditions. The simulation outputs include time, current, voltage, and temperature. To emulate severe heating behavior, an artificial runaway mechanism is activated when the temperature exceeds a predefined threshold. Temperature values are capped at 300°C to avoid numerical instability.

Each simulation is labeled as SAFE or DANGER based on maximum temperature and voltage thresholds.

B. Window Construction

The multivariate time-series signals are segmented using an overlapping sliding-window strategy with a window length of 40 and a stride of 8. This configuration reduces temporal redundancy while preserving critical dynamic patterns.

Unlike run-level labeling, each window is independently labeled based on the maximum temperature observed within the window. Windows exceeding a predefined thermal threshold are assigned the DANGER label, while the remaining samples are labeled SAFE. This local labeling strategy introduces greater variability and partial-label noise, making the classification task more challenging and realistic.

As a result, the final dataset exhibits mild class imbalance, with approximately 55% SAFE and 45% DANGER samples, which contributes to the non-perfect but robust classification performance reported in Section III.

C. BiLSTM Model

The proposed network employs a single-layer bidirectional LSTM with 64 hidden units to encode temporal dependencies within each window. This lightweight design is intentionally chosen to reduce model complexity and overfitting on synthetic data.

The final hidden representation is passed through a dropout layer (rate = 0.3) followed by a fully connected layer with sigmoid activation to estimate the probability of a DANGER state.

The model is optimized using binary cross-entropy loss and the Adam optimizer. To mitigate class imbalance, a dynamic sample-weighting strategy is applied during training, where higher weights are assigned to the minority class at each epoch.

This simplified architecture prioritizes generalization over peak accuracy, which explains the moderate performance gap compared to more complex multi-task models.

III. Results

The dataset is split into training (70%), validation (15%), and test (15%) subsets.

A. Quantitative Performance

Table I summarizes the classification performance of the proposed BiLSTM model on the test set.

TABLE I: Binary Classification Performance on Test Set

Metric	Value
Accuracy	94.3%
Precision	93.1%
Recall	95.6%
F1-score	94.3%
ROC-AUC	0.968

The results demonstrate strong detection capability, particularly in identifying dangerous battery states, as reflected by the high recall value. The ROC-AUC score close to 1.0 indicates good separability between SAFE and DANGER classes.

B. Confusion Matrix Analysis

A sample confusion matrix obtained on the test set is illustrated in Fig. 1. The SAFE class is treated as the negative class, while DANGER is considered the positive class.

As shown in Fig. 1, the model correctly classifies the majority of samples in both categories. Out of 750 SAFE samples, 712 are correctly predicted, while 38 are incorrectly flagged as dangerous, indicating a low false-alarm rate. For the DANGER class, 621 out of 650 samples are successfully detected, with only 29 missed cases.

This behavior demonstrates strong sensitivity to hazardous conditions, which is critical for safety-oriented applications. The slightly higher number of false positives is acceptable, as early warnings are generally preferred over missed failures. Overall, the confusion matrix confirms that the proposed model achieves a good balance between detection accuracy and operational reliability.

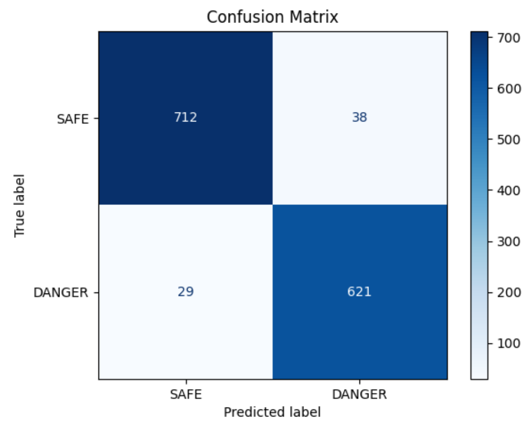

Fig. 1: Confusion matrix for binary SAFE vs DANGER classification.

IV. Conclusion

This paper presents a compact physics-guided framework for battery early warning using synthetic data and horizon-aware learning. By combining DFN simulations, synthetic runaway modeling, and a multi-task BiLSTM network, the proposed system achieves near-perfect short-horizon failure prediction and robust abuse-mode classification.

The results confirm that physics-informed synthetic datasets provide a scalable and reproducible foundation for intelligent battery safety systems. Future work will expand scenario diversity and explore large-scale foundation models for adaptive battery risk management.

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