ThermaGuard: A Physics-Based Deep Learning Approach to Thermal Runaway in EV Batteries

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***Abstract*—Thermal runaway in lithium-ion batteries poses serious safety risks, especially in electric vehicles. This paper presents *ThermaGuard*, a physics-guided long short-term memory (LSTM) model that integrates Joule heating-based predictions with residual learning to improve battery temperature forecasting. By combining physics-based insights with deep learning, *ThermaGuard* enhances accuracy and interpretability. Evaluated against a standard LSTM using real battery datasets, *ThermaGuard* achieved over 5% improvement in RMSE and MAE. Results show its strong generalization and potential for early thermal anomaly detection, offering a safer and more reliable foundation for battery management systems.**

***Index Terms*—thermal runaway, battery, overheating, EVs, Physics**

I. Introduction

Lithium-ion batteries are central to powering electric vehicles (EVs), due to their high energy density and long cycle life [1]. However, their operation presents critical safety challenges, particularly the risk of thermal runaway, a condition in which excessive internal heat leads to uncontrollable temperature rise, potentially resulting in fire or explosion [2]. This risk is exacerbated in EVs, where dynamic operating conditions and high current loads can accelerate thermal instabilities [3].

Current battery management systems (BMS) monitor temperature using onboard sensors, but most lack the ability to predict thermal runaway events before they escalate [4]. Recent data-driven approaches, particularly long short-term memory (LSTM) networks, have shown promise in modeling battery thermal behavior [5]. However, these models often fail to generalize under unseen conditions and do not account for the underlying physical mechanisms driving heat generation, such as Joule heating [3].

To address this gap, this study proposes ***ThermaGuard***, a physics-guided LSTM framework that combines a first-principles thermal model with deep learning through residual learning. The physics-based component estimates baseline temperature trend based on current and internal resistance, while the LSTM model learns the residual deviations caused by nonlinear or unmodeled effects.

ThermaGuard's performance was evaluated against a standard LSTM model using real-world high-temperature battery datasets. Results demonstrated that integrating physics into the learning process significantly enhanced thermal prediction, enabling more robust early-warning systems for battery safety.

II. Methodology

ThermaGuard consists of two main components: (i) A **physics-based model** that estimates temperature rise due to Joule heating effects. (ii) **residual LSTM model** that learns the deviation between observed and physics-predicted temperatures. The final prediction is obtained by summing the output of the physics model and the learned residual, thereby improving both accuracy and interpretability. The overall system architecture is illustrated in Fig. 1.

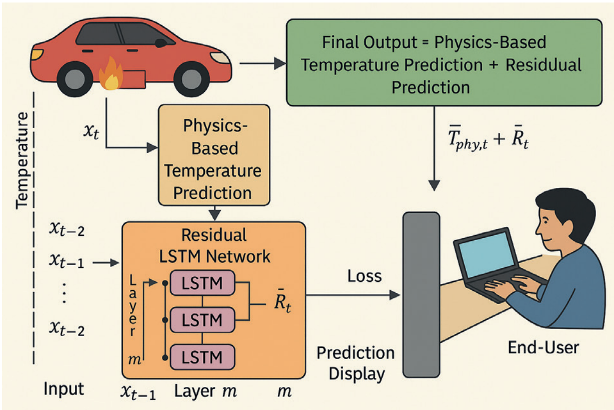

Fig. 1. ThermaGuard architecture for thermal runaway prediction in lithium-ion batteries.

A. Physics-Based Temperature Estimation

The initial temperature estimation is based on Joule heating principles. The heat generated within the battery is calculated as: $Q = I^2R$, where: Q is the heat generation (in watts), I is the battery current (in amperes), and R is the internal resistance (in ohms).

The temperature prediction from the physics model may be expressed as: $T_{\text{phy}} = T_{\text{amb}} + k \cdot Q$, where: T_{phy} is the physics-based temperature estimate, T_{amb} is the ambient temperature, k is a thermal proportionality constant.

B. Residual Learning with LSTM

The residual between the actual and predicted temperature by physics may be defined as: $\mathcal{R} = T_{\text{true}} - T_{\text{phy}}$

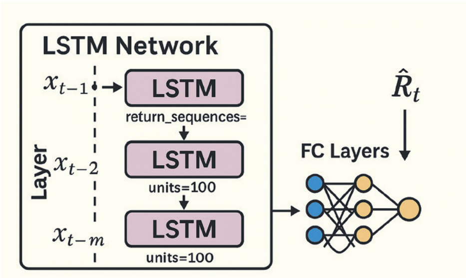

Fig. 2. LSTM model architecture.

A long-short-term memory (LSTM) network was trained to predict this residual $\hat{\mathcal{R}}$ based on historical battery data. The LSTM captures temporal dependencies and non-linear behavior not modeled in the physics-based component. The LSTM model is illustrated in Fig. 2.

TABLE I
DATASET AND TRAINING CONFIGURATION FOR THERMAGUARD

Component	Details
Dataset Source	Battery-M dataset [6]
Cell Used	Battery-M (80% capacity after 1158 cycles)
Features	Temperature, Current, Resistance
Normalization	Min-max scaling
Train-Test Splits	80:20
Optimizer	Adam
Epochs	20
Batch Size	32
Framework	TensorFlow 2.10 (Python 3.10)
Hardware	Intel i5, 32 GB RAM, GTX 1650 GPU

The final ThermaGuard temperature prediction is then calculated as:$T_{\text{pred}} = T_{\text{phy}} + \hat{\mathcal{R}}$ This formulation ensures that the prediction remains grounded in physical principles while adapting to real-world non-linearities and uncertainties.

The model was trained using the mean squared error (MSE) between predicted and true temperatures: $\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}(T_{\text{true},i} - T_{\text{pred},i})^2$. This loss encourages the model to reduce both the systematic error of the physics model and the learned deviations. The dataset and training configuration used in this study is described in Table I.

III. RESULTS

Table II shows that *ThermaGuard* consistently outperformed the standard LSTM model across all metrics. Specifically, it achieved a lower MSE (0.0075 vs. 0.0084), RMSE (0.0866 vs. 0.0916), and MAE (0.0679 vs. 0.0734), representing over 5% improvement in both RMSE and MAE. Additionally, the R^2 score improved from 0.842 to 0.860, demonstrating stronger predictive power and generalization.

TABLE II
PERFORMANCE COMPARISON BETWEEN LSTM AND *ThermaGuard*

Model	MSE	RMSE	MAE	R^2
Standard LSTM	0.0084	0.0916	0.0734	0.842
ThermaGuard	**0.0075**	**0.0866**	**0.0679**	**0.860**

Figure 3 visualizes the comparison between predicted battery temperatures from both models. The *ThermaGuard* model's predictions closely follow the actual temperature trend, especially during high-variance periods, indicating improved learning of thermal dynamics and better risk estimation under fluctuating loads.

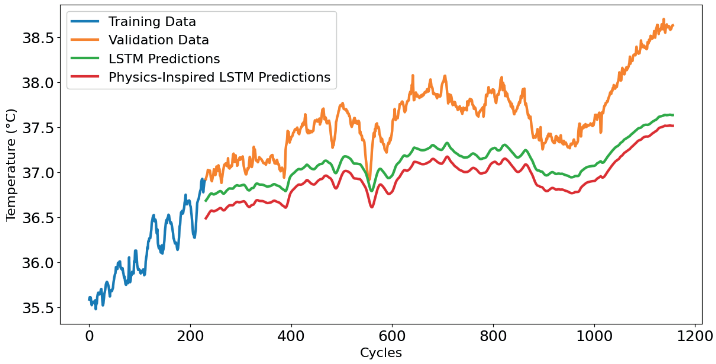

Fig. 3. Performance comparison of standard LSTM and ThermaGuard on Battery-M dataset

IV. CONCLUSION

This study proposed *ThermaGuard*, a physics-guided LSTM model that combines Joule heating principles with residual learning. It outperformed standard LSTM with over 5% improvement in RMSE and MAE, offering improved accuracy for battery thermal safety prediction.

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REFERENCES

[1] J. N. Njoku, C. I. Nwakanma, and D.-S. Kim, "Explainable data-driven digital twins for predicting battery states in electric vehicles," *IEEE Access*, vol. 12, pp. 83 480–83 501, 2024.
[2] J. N. Njoku, E. C. Nkoro, R. M. Medina, C. I. Nwakanma, J.-M. Lee, and D.-S. Kim, "Leveraging digital twin technology for battery management: A case study review," *IEEE Access*, vol. 13, pp. 21 382–21 412, 2025.
[3] S. Kumar and H.-J. Kim, "Recent advances in early warning methods and prediction of thermal runaway events in li-ion batteries," *Journal of Industrial and Engineering Chemistry*, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1226086X24007184
[4] J. N. Njoku, C. I. Nwakanma, J.-M. Lee, and D.-S. Kim, "Model comparison and selection for battery digital twin development using pybamm," in *The 33rd Joint Conference on Communication and Information (JCCI)*, 2023, pp. 1–2.
[5] S. Zhu, C. He, N. Zhao, and J. Sha, "Data-driven analysis on thermal effects and temperature changes of lithium-ion battery," *Journal of Power Sources*, vol. 482, p. 228983, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775320312829
[6] K. A. Severson, P. M. Attia, N. Jin, N. Perkins, B. Jiang, Z. Yang, M. H. Chen, M. Aykol, P. K. Herring, D. Fraggedakis, M. Z. Bazant, S. J. Harris, W. C. Chueh, and R. D. Braatz, "Data-driven prediction of battery cycle life before capacity degradation," *Nature Energy*, vol. 4, no. 5, pp. 383–391, 2019. [Online]. Available: https://doi.org/10.1038/s41560-019-0356-8