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ARTIFICIAL INTELLIGENCE-BASED EARLY PREDICTION OF THERMAL RUNAWAY IN AGV BATTERY CELLS

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ABSTRACT

Automated Guided Vehicles (AGVs) in semiconductor manufacturing operate continuously with lithium-ion battery packs which undergo thermal runaway under abusive conditions such as over-charge, over-discharge or cooling failure. This study presents an artificial-intelligence (AI) - based early - warning framework that predicts imminent thermal runaway in AGV battery cells. We collected a large-scale dataset of 12.7 million time-series records from the battery-management system (BMS) of AGVs in the real factory environment, including cell-level temperature, voltage, current, alarms and cycle counts information. Three predictive models — XGBoost, 1D CNN and LSTM — were developed to forecast the next-step maximum cell temperature using a 24-minute sliding window. LSTM achieved the best performance (MAPE ≈ 1.66 %) compared to CNN (≈ 1.67 %) and XGBoost (≈ 1.76 %). Based on LSTM residuals and predicted threshold exceedance, an early warning mechanism was implemented, raising alarms several minutes before the temperature crossed critical limits. The results demonstrate that AI-driven forecast algorithm enables practical pre-runaway warning and can be embedded in AGV safety-monitoring systems in high-throughput semiconductor logistics applications.

Keywords: *Thermal runaway, Lithium-ion battery, Automated Guided Vehicle (AGV), LSTM, CNN, XGBoost, Early warning, Battery management system (BMS)*

1. INTRODUCTION

1.1 Background and motivation

Batteries used in industrial Automated Guided Vehicles (AGVs) are predominantly lithium-ion cells, which are susceptible to thermal runaway under abusive conditions such as overcharging, over-discharging, internal short circuits, or cooling system failure. Thermal runaway is a self-accelerating process in which rapid internal heat generation leads to venting, fire, or explosion, posing serious risks to human safety and industrial operations [1]. Recent large-scale battery fire incidents reported worldwide, including those in South Korea, have highlighted the limitations of conventional battery management systems that rely on fixed threshold-based protection schemes and often fail to provide sufficient early warning prior to catastrophic failure [2]. In semiconductor packaging (PKG) logistics lines, AGVs operate continuously near personnel and high-value manufacturing equipment. An unexpected battery cell failure may therefore cause not only fire hazards but also unplanned production downtime. Consequently, predictive technologies capable of detecting early-stage abnormal behavior and forecasting imminent thermal runaway before irreversible escalation are urgently needed. Recent advances in artificial intelligence enable data-driven analysis of complex battery behavior, offering a promising approach for early prediction and proactive safety management in AGV battery systems [3].

Figure 1 illustrates a representative temperature escalation profile of a lithium-ion AGV cell during charging. At point T1, the cell reaches the critical temperature threshold; after T1, cell temperature rises sharply and thermal runaway occurs.

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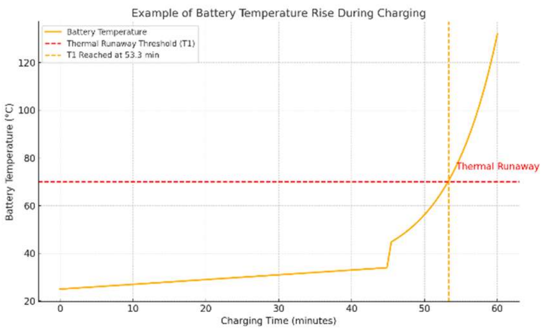

Figure 1: Thermal runaway temperature profile of AGV battery cell

Conventional battery safety management typically relies on predefined thresholds: alarms are triggered only when temperature or voltage exceeds safety limits. Such reactive schemes often fail to provide sufficient lead time because thermal runaway evolves rapidly. Recently, AI-driven data-centric prediction models have been proposed to detect early signs of runaway and warn operators in advance [4-6]. The objective of this study is to develop an AI model capable of early prediction of AGV cell thermal runaway using large-scale real-world BMS (Battery Management System) data, and to validate its feasibility for real-time early warning in an industrial environment.

To this end, we collected approximately 12.7 million BMS records from AGV equipment deployed in a semiconductor manufacturing facility, including cell-level temperature and voltage time series as well as anomaly types, zone information, alarm history, pack identifiers, and charge cycle counts. Using this dataset, we trained and compared three modeling approaches: eXtreme Gradient Boosting (XGBoost), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks. The final goal is to identify the most accurate predictor and utilize it as the core algorithm for an early-warning module in AGV battery safety management.

1.2 Contributions and research organization

The contributions of this paper are as follows. First, this research constructs a large-scale dataset of industrial AGV battery usage, which has been rarely addressed in prior work, and develops a predictive model for thermal runaway using real-time operational BMS data exceeding 12 million records. Second, we perform a systematic comparison between machine learning (XGBoost) and deep learning (CNN, LSTM) models to quantify their relative strengths for early thermal runaway prediction. Third, we propose an early-warning mechanism based on the best-performing model and analyze its practical alert lead time using prediction residuals.

The remainder of this paper is organized as follows. Section 2 reviews related work on battery anomaly detection, thermal runaway early warning, and time-series forecasting models. Section 3 describes the industrial AGV dataset, data acquisition process, and preprocessing pipeline. Section 4 details the model architectures, hyperparameters, and evaluation metrics. Section 5 reports and analyzes the experimental results, including early-warning performance. Section 6 concludes the paper and discusses future work.

2. THEORETICAL BACKGROUND

2.1 Battery anomaly detection and early warning

Research on early anomaly detection in lithium-ion batteries has evolved along three axes: experiment-driven, model-driven, and data-driven approaches [7]. Experiment-driven studies physically stress cells under overheat or overload conditions to identify critical temperatures and safe operating envelopes. Calorimetry and gas analysis have been used to characterize internal heat generation and determine runaway thresholds [7]. These methods provide clear physical insight but are costly, hazardous, and difficult to scale [8-10].

Model-driven approaches formulate electrochemical or thermo-fluid models to estimate internal temperature rise and predict imminent runaway [8]-[10]. For example, equivalent circuit models coupled with heat generation equations can infer core temperature, while CFD-based simulations estimate pack-level thermal distribution and runaway risk under specific conditions [8-10]. Such physics-based models require careful parameter identification and often struggle to generalize to highly dynamic industrial environments [11][12].

Data-driven approaches leverage real-time BMS telemetry to learn correlations between sensor signals (temperature, voltage, current, alarms) and future runaway behavior [4][5]. Deep learning has enabled extraction of latent precursors of runaway from large, noisy time-series data, even without explicit electrochemical modeling [4][5]. However, true runaway events are rare in practice, creating a severe class imbalance [6]. Prior work has explored synthetic data augmentation, few-shot/meta-learning, and unsupervised anomaly detection (e.g., autoencoders using reconstruction errors as anomaly indicators) to mitigate data sparsity [6][13][14].

From an operational safety viewpoint, the key metric is not only whether runaway is detected, but how early. Cheng et al. proposed an LSTM–TCN-based predictor for EV charging that forecasts future temperature trajectories and raises alarms by analyzing residuals between predicted and measured temperatures [15]. Their LSTM-based model provided earlier warnings than a conventional BMS threshold trigger. This demonstrates that data-driven forecasting can detect risk several minutes in advance, creating valuable response time for shutdown or isolation procedures [15].

Table 1: Summary of prior studies on thermal runaway prediction

Approach	Description	Advantages	Limitations	References
Experiment-driven	Tests cells under overheating/overloading to find runaway thresholds.	Clear physical insight.	Costly, unsafe, hard to scale.	[7][10]
Model-driven	Simulates thermal behavior via electrochemical or thermal models.	Theoretical prediction with less data.	Complex, limited generalization.	[11] [12]
Data-driven	Learns anomaly patterns from BMS and AI data.	Real-time detection.	Data imbalance.	[4][5]
Enhanced data-driven	Uses augmentation or meta-/unsupervised learning.	Higher accuracy.	Needs quality data.	[6] [13] [14]
Early-warning systems	Predicts future temperature via deep models (e.g., LSTM–TCN).	Faster alerts.	Threshold tuning required.	[15]

2.2 Time-series prediction models

2.2.1 LSTM model

Deep learning for time-series forecasting has accelerated adoption of advanced AI in thermal runaway prediction. Long Short-Term Memory (LSTM) networks, originally introduced to overcome the vanishing gradient problem in recurrent neural networks, can learn long-term temporal dependencies through gated memory cells [3]. LSTM has been successfully applied to battery state estimation and internal temperature prediction, outperforming classical observers by reducing RMSE by approximately 1.5% in marine lithium-ion battery applications [16]. LSTM is therefore well suited to capture gradual heat buildup and subtle precursors of runaway in AGV cells.

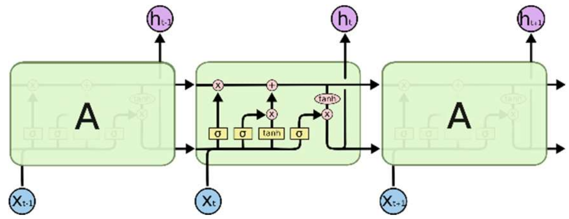

Figure 2: LSTM architecture

2.2.2 CNN model

Convolutional Neural Networks (CNNs), though widely known for image processing, can also model 1-D signals by extracting local temporal patterns. CNN filters can detect rapid temperature spikes, oscillatory noise, and short-term gradients in sensor data. Hybrid CNN–LSTM architectures have been used to predict remaining useful life (RUL) and state-of-health (SOH) in batteries, achieving high accuracy by combining local feature extraction with long-term dependency modeling [17],[18]. In addition, CNN features can be fed into boosted tree regressors such as XGBoost to improve early-life degradation prediction [19].

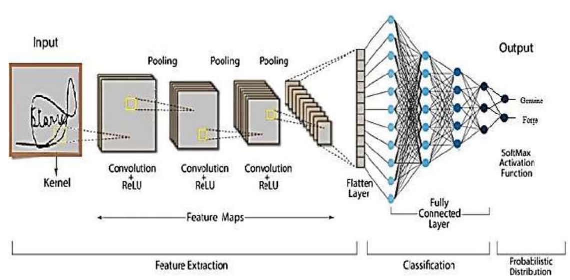

Figure 3: CNN architecture

2.2.3 XGBoost model

Tree-based ensemble learners such as XGBoost offer strong predictive accuracy and robustness with relatively low computational cost. XGBoost implements efficient gradient boosting of decision trees and has demonstrated superior performance in tasks such as battery state-of-health estimation, in some cases achieving sub-1% RMSE when combined with Bayesian hyperparameter optimization [20]. Although XGBoost does not explicitly encode sequential structure, providing a sufficiently long sliding window of historical sensor values allows it to approximate temporal trends.

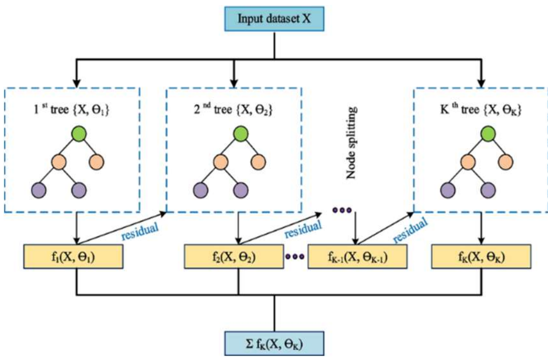

Figure 4: XGBoost architecture

2.2.4 Model summary

The three time-series prediction models employed in this study—XGBoost, CNN, and LSTM—are compared and summarized in Table 2.

Table 2: Comparison of time-series prediction models

Model	Description	Advantages	Limitations	References
LSTM	Recurrent neural network with gated memory cells capturing long-term dependencies.	Captures gradual heat rise; accurate forecasting.	Needs large data, slow training.	[3] [16]
CNN	Extracts local temporal features from 1-D signals using convolutional filters.	Detects rapid spikes; works well with LSTM.	Weak in long-term modeling.	[17] [19]
XGBoost	Gradient-boosted decision trees for regression/classification.	High accuracy; low cost.	No sequential awareness.	[20]

The field of early prediction of battery thermal runaway has been shifting from physics-based modeling approaches toward data-driven methods, with deep learning techniques—particularly long short-term memory (LSTM) networks—receiving increasing attention due to their superior predictive performance [15]. In this context, this study compares the performance of three representative models—XGBoost, convolutional neural networks (CNNs), and LSTM—and validates the effectiveness of an LSTM-based deep learning early warning system for battery thermal runaway.

2.3 Research Hypothesis

In time-series prediction of AGV battery temperature, this study hypothesizes that the LSTM model achieves the lowest mean absolute percentage error (MAPE), followed by CNN and XGBoost. This hypothesis is motivated by LSTM's ability to capture both short- and long-term temporal dependencies in battery temperature dynamics, whereas CNN primarily captures local patterns and XGBoost lacks explicit temporal modeling capability.

2.4 Semiconductor Manufacturing Logistics System Configuration

2.4.1 Logistics Equipment Control System

The automatic material handling control system consists of device controllers, which control individual transport units, and transport controllers, which manage and coordinate the entire transport network. The operational logic of the automated control system is illustrated in Figure 4. When the upper control system issues a transport command based on production plans, product information, and equipment status, the logistics system determines the optimal transport route considering the status of all devices and transmits it to the device controller. The transport unit then executes material transfer to the designated destination accordingly.

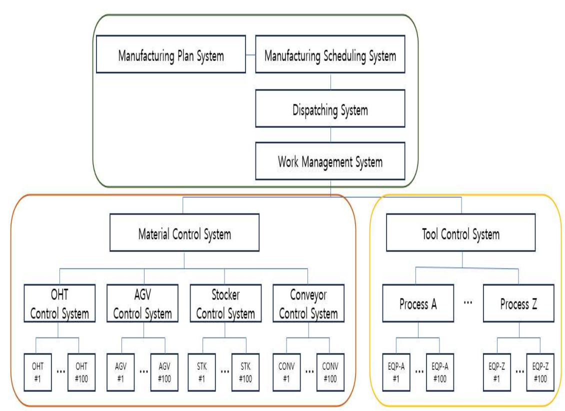

Figure 4: Automation Line System Configuration

2.4.2 Automated Guided Vehicle (AGV)

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In semiconductor manufacturing lines, Automated Guided Vehicles (AGVs) are employed to enhance production efficiency and operational safety through automated material transport. The AGV autonomously transfers materials between processes, while its battery condition is continuously monitored by the Battery Management System (BMS). The BMS collects key parameters such as voltage, current, temperature, and charge–discharge status to ensure battery safety and performance. These BMS data are integrated with AGV operational information through a central control system and used as input for an AI-based prediction model to detect early signs of thermal runaway or other anomalies. This integrated data acquisition approach strengthens the reliability of semiconductor logistics lines and enables predictive maintenance.

Figure 5: AGV in semiconductor line

3. RESERCH METHODOLOGY

This study proposes an artificial intelligence–based data analysis methodology for the early prediction of thermal runaway in AGV battery cells. The methodology begins with the installation of temperature sensors integrated with the battery management system (BMS) at the start of AGV operation, followed by continuous acquisition of battery cell temperature data throughout the entire operational period. The collected time-series data undergo preprocessing, including outlier removal, missing value imputation, and normalization. To mitigate class imbalance between normal and abnormal operating conditions, data balancing techniques are applied. Subsequently, battery temperature dynamics are learned and future temperature trends are predicted using XGBoost-, CNN-, and LSTM-based prediction models. Based on the prediction results, anomaly classification is performed to assess the risk of thermal runaway. The classification outcomes are then fed back into the BMS monitoring and battery management stages, contributing to enhanced operational safety of the AGV system. By integrating AI-based prediction with anomaly classification, the proposed methodology aims to overcome the limitations of conventional threshold-based BMS approaches. The overall research methodology process is illustrated in Figure 6.

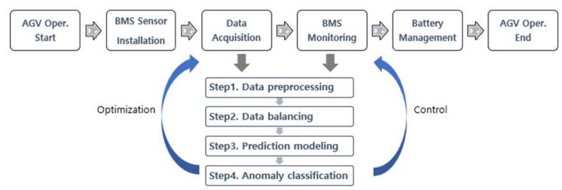

Figure 6: Research Methodology

4. DATA ACQUISITION AND PREPROCESSING

4.1 Sensor configuration and logging architecture

We collected data from lithium-ion battery packs physically installed on AGVs operating in a semiconductor factory logistics line. The AGV Battery Management System (BMS) continuously monitors per-cell temperature (°C), voltage (V), and current, and records anomaly alarms. In addition, metadata such as pack ID/type, installation zone, alarm category, and charge cycle count are logged. The deployed AGV packs consist of more than 100 cells, and long-term operation over several months produced a total of 12,718,990 records. Each cell therefore contributes tens of thousands of timestamped measurements.

Data acquisition was performed by exporting logs from the AGV monitoring server. Each AGV contains multiple battery cells wired in series/parallel, managed by a pack-level BMS controller. The controller samples each cell's voltage and temperature at approximately one-minute intervals and transmits the values either locally or to a central server. When an abnormal event occurs (e.g., rapid temperature rise beyond a preset threshold, voltage imbalance, charge completion), the BMS also records the corresponding alarm code and timestamp. This study therefore incorporates both nominal operation data and abnormal-event snapshots for correlation analysis with pre-runaway signatures.

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Table 3: Data columns used in this study

Column Name	Description	Sample	Unit	Data Type
LINE_ID	Line	4L	-	VARCHAR2(64 BYTE)
SERIAL_NUM	Serial Number	BT241062208029	-	VARCHAR2(64 BYTE)
BATTERY_RATE	SoC	95.3	%	NUMBER
DEVICE_ID	Vehicle ID	41TAGV67	-	VARCHAR2(64 BYTE)
BATTERY_TYPE	Maker	PS	-	VARCHAR2(10 BYTE)
CHARGE_CURRENT	Charging Current	80	10mA	NUMBER
DISCHARGE_CURRENT	Discharging Current	1100	10mA	NUMBER
CYCLETIME	Battery Life	27231	hour	NUMBER
VOLTAGE_RATE	Voltage Rate	28.16	V	NUMBER
HIGHEST_CELL	Maximum Cell Voltage	4154	mV	NUMBER
LOWEST_CELL	Minimum Cell Voltage	4153	mV	NUMBER
HIGHEST_TEMP	Maximum Cell Temperature	26	℃	NUMBER
LOWEST_TEMP	Minimum Cell Temperature	25	℃	NUMBER
MAX_VOLUME	Battery Capacity	106	A	NUMBER
PACK_INFO	Cell Balancing Value	31		NUMBER
CELL1_TEMP	Cell #1 Temperature	25	℃	NUMBER
CELL2_TEMP	Cell #2 Temperature	26	℃	NUMBER
CELL3_TEMP	Cell #3 Temperature	26	℃	NUMBER
CELL4_TEMP	Cell #4 Temperature	26	℃	NUMBER
CELL5_TEMP	Cell #5 Temperature	25	℃	NUMBER
CELL6_TEMP	Cell #6 Temperature	26	℃	NUMBER
CELL7_TEMP	Cell #7 Temperature	26	℃	NUMBER
CELL1_VOLTAGE	Cell #1 Voltage	4154	mV	NUMBER
CELL2_VOLTAGE	Cell #2 Voltage	4154	mV	NUMBER
CELL3_VOLTAGE	Cell #3 Voltage	4154	mV	NUMBER
CELL4_VOLTAGE	Cell #4 Voltage	4154	mV	NUMBER
CELL5_VOLTAGE	Cell #5 Voltage	4154	mV	NUMBER
CELL6_VOLTAGE	Cell #6 Voltage	4153	mV	NUMBER
CELL7_VOLTAGE	Cell #7 Voltage	4154	mV	NUMBER
CHARGEPANEL_LP_TEMP	Left Charging Pad (+)	23	℃	NUMBER
CHARGEPANEL_LM_TEMP	Left Charging Pad (-)	23	℃	NUMBER
CHARGEPANEL_RP_TEMP	Right Charging Pad (+)	23	℃	NUMBER
CHARGEPANEL_RM_TEMP	Right Charging Pad (-)	23	℃	NUMBER
BATTERY_TEMP1	Maximum Cell Voltage	26	℃	NUMBER
CREATE_TIME	Create Time	2025-02-13 0:24	-	DATE

Raw logs were originally organized by AGV unit, battery pack, and cell. We merged these into a unified dataset synchronized on timestamps. Each record was tagged with cell ID and pack ID. Missing values due to intermittent sensor dropouts were forward-filled or removed, and unphysical outliers (e.g., voltage spikes beyond feasible limits) were filtered.

4.2 Preprocessing and feature engineering

To prepare inputs for model training, we normalized temperature and voltage signals using min–max scaling or z-score standardization. Because trends and gradients are more informative than absolute magnitudes, normalization prevents certain sensors from dominating the loss purely due to scale differences.

We then applied a sliding-window approach. For each training sample, we extracted W=24 consecutive minutes of telemetry (temperature, voltage, current, and engineered features such as gradients). The task for all models was to predict the next-step maximum cell temperature. Although LSTM can naturally ingest sequences, we used the same fixed-length window for all models for fair comparison.

Instead of directly classifying 'runaway / no-runaway' which suffers from extreme class imbalance, we cast the problem as short-horizon temperature forecasting. Early-warning logic is then derived from prediction residuals and predicted threshold exceedance. Datasets were split chronologically into training (70%), validation (15%), and test (15%) segments to avoid temporal leakage. The test segment included abnormal events

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such as sharp cell temperature surges, enabling evaluation under realistic pre-runaway conditions.

temperature acceleration, and is computationally efficient for deployment.

Table 4: Preprocessing Data Sample

battery_rate	create_time	battery_type	cycletime	voltage_rate	highest_cell	lowest_cell	highest_temp	lowest_temp	max_volume	cell1_temp
95.6	2025-01-15 0:00	PS	27274	28.59	4089	4080	24.2	24.2	106	24.2
98.9	2025-01-15 0:00	BT	14408	28.6	4101	4091	26	24	106	25
99.9	2025-01-15 0:00	BT	18465	28.6	4103	4091	30	28	106	30
99.9	2025-01-15 0:00	BT	7239	29	4151	4151	23	21	106	23
100	2025-01-15 0:00	BT	5406	29	4157	4156	26	25	106	25
99.9	2025-01-15 0:00	BT	2825	28.6	4111	4083	25	23	106	23
99.9	2025-01-15 0:00	BT	5224	28.9	4135	4134	25	24	106	24
96.5	2025-01-15 0:00	PS	29128	28.49	4077	4069	21.7	21.7	106	21.7
99.8	2025-01-15 0:00	BT	5418	28.7	4107	4098	27	26	106	26
93.4	2025-01-15 0:00	PS	28335	28.35	4054	4048	23.4	23.4	106	23.4
99.9	2025-01-15 0:00	BT	18218	28.6	4103	4094	27	25	106	25
100	2025-01-15 0:00	BT	5403	29	4151	4150	28	26	106	27
99.9	2025-01-15 0:00	BT	18280	29	4144	4144	30	27	106	27
99.7	2025-01-15 0:00	BT	14135	28.7	4105	4098	27	25	106	27
99.9	2025-01-15 0:00	BT	18983	28.6	4102	4095	23	21	106	22
99.9	2025-01-15 0:00	BT	4981	29.5	4233	4168	33	31	106	32
65.3	2025-01-15 0:00	PS	8803	25.99	3717	3712	25.1	25.1	106	25.1
99.9	2025-01-15 0:00	BT	18419	28.7	4106	4097	30	28	106	29
98	2025-01-15 0:00	PS	4204	28.63	4092	4087	25.1	25.1	106	25.1
97.9	2025-01-15 0:00	PS	26754	28.99	4144	4138	26	26	106	26

5. MODEL EXPERIMENTS

5.1 Model architectures

5.1.1 XGBoost model

The XGBoost model is a gradient-boosted decision tree ensemble trained in regression mode to predict the next-step temperature [20]. We flattened each 24-minute window into a feature vector. Key hyperparameters such as learning rate (0.1), max_depth (6), number of estimators (100), subsample (0.8), and colsample_bytree (0.8) were tuned using the validation set. Early stopping with patience 10 rounds was applied to mitigate overfitting. Although XGBoost does not explicitly model temporal order, providing a sufficiently long window enables it to partition the feature space according to important temporal signatures.

5.1.2 CNN model

The CNN model is a 1D convolutional network with two convolutional layers (64 and 32 filters, kernel size=3), one max-pooling layer (pool size=2), and two fully connected layers (64 units then 1 output). ReLU activations were used. CNN excels at capturing local bursts such as sharp

5.1.3 LSTM model

The LSTM model is a two-layer bidirectional LSTM with 128 hidden units per layer and dropout=0.1. The final hidden state is passed through a dense layer to regress the next-step temperature. We optimized the network using Adam with learning rate 0.001. Bidirectionality helps encode both forward and backward temporal relationships within each 24-minute window [16].

Table 4: Hyperparameter settings for XGBoost, CNN, and LSTM

Model	Architecture	Key parameters	Training settings
LSTM	2-layer Bidirectional LSTM	hidden_dim=128, dropout=0.1	Adam(lr=0.001), epochs=20, batch=256
CNN	Conv1D(64, k=3) → MaxPool → Conv1D(32, k=3) → FC	ReLU, fc1=64 → fc2=1	Adam(lr=0.001), epochs=20, batch=256
XGBoost	Gradient Boosting Regression Tree	max_depth=6, n_estimators=100, learning_rate=0.1	early_stopping=10, subsample=0.8

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5.2 Training setup and evaluation metrics

All models were trained on Ubuntu 20.04 with dual NVIDIA A6000 GPUs, Python 3.10.16, and PyTorch 2.1. Batch size was 256. We computed four regression metrics on the held-out test set: Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). For actual value y, prediction ŷ, and sample count N:

- MSE = (1/N) Σ (y-ŷ)^2
- MAE = (1/N) Σ |y-ŷ|
- RMSE = sqrt((1/N) Σ (y-ŷ)^2)
- MAPE = (100/N) Σ |(y-ŷ)/y|

We prioritized MAPE for model selection because it expresses error as an interpretable percentage for industrial stakeholders. Extremely low-temperature values (near 0°C), which destabilize MAPE, were filtered or replaced with a small epsilon.

6. MODEL EXPERIMENTS

6.1 Model architectures

Table 5 summarizes test-set performance for XGBoost, CNN, and LSTM across all four-evaluation metrics. Lower values indicate better predictions. LSTM achieved the best scores across all metrics. In particular, MAPE was approximately 1.76% for XGBoost, 1.67% for CNN, and 1.66% for LSTM, indicating that LSTM delivered the lowest relative error. LSTM's advantage suggests that long-term temporal dependencies—such as gradual heat accumulation preceding a sharp spike—are critical for forecasting imminent runaway. CNN outperformed XGBoost on all metrics, likely because CNN captures short-term local heating patterns and noise suppression, while XGBoost relies solely on tabularized historical snapshots. Nevertheless, XGBoost still achieved industry-relevant accuracy and extremely fast training and inference.

We also examined error distributions. XGBoost occasionally exhibited large outliers when encountering unseen thermal behaviors, inflating RMSE relative to MAE. In contrast, LSTM produced uniformly low residuals over time. Statistical tests (two-sample t-test on per-cell MAPE values) confirmed that the LSTM improvement over the other models is significant at the 95% confidence level ($p < 0.05$). Consequently, we selected LSTM as the preferred model for early-warning deployment.

Table 5: Performance evaluation results by model

Model	Evaluation metrics			
	MSE	MAE	RMSE	MAPE(%)
XGBoost	0.3738	0.6114	0.4794	1.7572
CNN	0.3381	0.4540	0.5815	1.6738
LSTM	0.3589	0.4531	0.5990	1.6645

6.2 Early-warning capability

Beyond accuracy, the practical objective is proactive safety. We implemented a residual-based anomaly detection logic using the LSTM predictor. The algorithm continuously monitors the residual (actual minus predicted next-step temperature) and its moving average. Under normal conditions, residuals remain small. As runaway initiates, temperature rises more rapidly than expected, causing residuals to increase sharply. When the moving average exceeded three times its nominal level, an alarm was issued. Additionally, if the predicted temperature itself was projected to exceed a predefined safety threshold (e.g., 60°C), an immediate alarm was triggered. In test scenarios with real abnormal events, this scheme typically raised warnings up to about 5 minutes before the measured temperature crossed the critical limit, enabling safe AGV shutdown or pack isolation. These findings align with prior work showing that LSTM-based forecasting can outperform traditional BMS threshold alarms in early detection [15],[16].

7. CONCLUSION AND FUTURE WORK

7.1 Conclusion

In this study, artificial intelligence–based models for the early prediction of thermal runaway in AGV battery cells were developed and comparatively analyzed. More than 12.72 million real-world operational data points collected from the battery management systems (BMSs) of AGVs operating in a semiconductor manufacturing facility were utilized. Three predictive models were constructed: XGBoost, a decision tree–based ensemble model; a convolutional neural network (CNN); and a long short-term memory (LSTM) recurrent neural network.

The experimental results indicate that the LSTM model achieved the highest prediction accuracy, exhibiting the lowest mean absolute percentage error (MAPE) of approximately 1.66%, followed by the CNN model, whereas XGBoost showed relatively larger prediction errors. The superior performance of the LSTM model is attributed to its ability to effectively learn both long-term and short-term patterns embedded in time-series battery temperature and voltage data, thereby enabling accurate identification of early thermal runaway signatures. Furthermore, an early warning algorithm based on LSTM prediction outputs was implemented, and the LSTM-based system demonstrated the highest detection rate and the lowest false alarm rate compared with the XGBoost- and CNN-based systems.

These results demonstrate that the LSTM-based deep learning model is the most suitable approach for early prediction of thermal runaway in AGV battery cells. When integrated into a BMS, such an AI model can analyze real-time sensor data streams and detect subtle abnormal patterns that may not be readily perceptible to human operators. This capability is expected to significantly contribute to the prevention of unexpected fire or explosion accidents in industrial environments, as well as to improvements in battery reliability and operational safety. Moreover, as similar battery safety issues have recently emerged in applications such as energy storage systems (ESSs) and electric vehicle charging infrastructure, the proposed methodology is expected to be applicable to a wide range of battery-powered systems.

Based on the findings of this study, a Battery Thermal-runaway Prediction System (BTPS) incorporating an LSTM-based artificial intelligence model is proposed for early detection of thermal runaway in AGV lithium-ion batteries, as illustrated in Fig. 7. The BMS is responsible for battery condition monitoring, cell balancing, overcharge protection, and thermal management, while the AGV Control System (ACS) manages AGV operation, status reporting, data storage, and database construction using data collected from the BMS. The proposed BTPS preprocesses the collected data, trains the LSTM model, detects abnormal behavior in real time, and provides visualization functions. When abnormal conditions are detected, an AGV shutdown command is issued via the ACS, and on-site fire response teams utilize the system monitoring results to perform timely intervention and preventive actions.

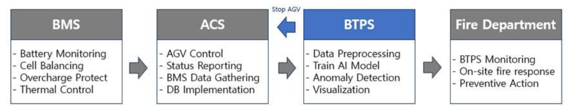

Figure 7: BTPS Configuration

7.2 Limitations and future work

Several limitations remain and point to directions for future research. First, thermal runaway events are extremely rare compared to normal operation, resulting in severe data imbalance. Future studies will incorporate targeted data augmentation, controlled experiments, and simulation-based stress testing to enrich rare-event samples [6]. Second, the current models focus on single-cell temperature forecasting; however, thermal propagation across cells and packs should be modeled using multi-cell approaches such as graph neural networks to capture spatial and thermal coupling effects. Third, interpretability is essential for industrial safety approval, and explainable artificial intelligence (XAI) techniques should be applied to provide clear justification for each issued alarm. Finally, real-time deployment requires embedded inference on AGV hardware under strict latency and memory constraints. Future extensions include probabilistic binary risk classification (e.g., “thermal runaway within X minutes”) and transformer-based sequence models, which may improve long-horizon prediction stability, scalability, and interpretability by capturing long-range temporal dependencies without explicit recurrence.

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