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A Comprehensive Review of Thermal Runaway Detection, Prognostics, and Intelligent Safety Management for Lithium-Ion Batteries

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Abstract: Lithium-ion battery technology is the most common energy storage technology for electric vehicles, portable electronics and energy storage systems. The electrochemical performance, long-cycle life, and high energy density make them ideal. The widespread use of high energy battery systems, however, raises the concern of the risk of thermal runaway (TR), which is one of the most significant safety challenges in the case of LIBs. A thermal runaway is an electrochemical chain reaction. They generate heat in a rapid manner, create toxic gases, spread a fire and eventually fire hazard. The conventional battery management system mainly relies on the voltage and temperature monitoring based on a threshold. This hardly gives any prior warning before catastrophic failure. Recently, the battery safety diagnosis and prognosis have been greatly implemented using various sensing technologies, machine learning, hybrid physics-informed modelling, and digital twin frameworks. The aim of this review article is to present early thermal runaway detection and prognostic safety management research in lithium-ion battery system. In the start of the article we have explained key mechanisms for thermal runaway initiation and propagation which are self-heating reactions, internal short circuits (ISC), thermal criticality, abuse condition and fire hazards. This review contains a brief summary of the Li-ion battery and the lithium-ion battery failure mechanisms. The next diagnostic techniques are analysed, electron microscopy, spectroscopy, scattering and X-ray, neutron and magnetic resonance imaging. A systematic review of early-warning signals and sensing technologies follows which includes voltage and current anomalies, embedded temperature sensing, gas evolution sensing, swelling, and force sensing, fibre-optic sensing, multimodal sensor fusion strategies. The review evaluates AI and ML modelling strategies for prognosis acceleration and uses such as conventional ML, deep learning, hybrid AI–physics, transfer learning and digital twin-enabled diagnosis. The final assessment addresses smart battery designs, IoT-enabled oversight, intelligent thermal management frameworks, and upcoming battery safety systems.

The future of battery safety systems will be increasingly sophisticated, with safety measures evolving from passive threshold-based protection to intelligent, self-adaptive, and prognostic safety systems capable of predicting runaway initiation conditions with sufficient warnings. Emerging developments in embedded multidimensional sensing, uncertainty-aware machine learning, digital twins, and state-of-safety methodologies are expected to play a central role in next-generation EV battery safety systems.

Keywords: Lithium-ion batteries; Thermal runaway; Early warning; Prognostics; Machine learning; Battery management systems.

I. INTRODUCTION

The rising requirement of electric vehicles and renewable energy systems has majorly increased the use of lithium-ion batteries (LIBs) across the world. Moreover, due to their attractive electrochemical features, high energy density, and long cycle life, they have been deployed on a large scale in transportation, aerospace, portable electronics, and stationary energy storage applications (Zhao et al., 2024). The high-energy lithium-ion systems which can greatly benefit from these batteries face numerous safety issues that have halted their further development.

According to experts, the thermal runaway is the most threatening failure mode of lithium-ion batteries. Thermal runaway is a runaway reaction process where the self-generated heat inside the battery exceeds the heat dissipation rate of the battery, leading to catastrophic failure. As a result, there is a potential increase in temperature, vent gas, fire propagation and explosion hazard (Feng et al., 2018). The substantial real-world impacts of uncontrolled TR propagation have been well illustrated by recent fire incidents of electric vehicles and large scale energy storage systems (Wang et al., 2022).

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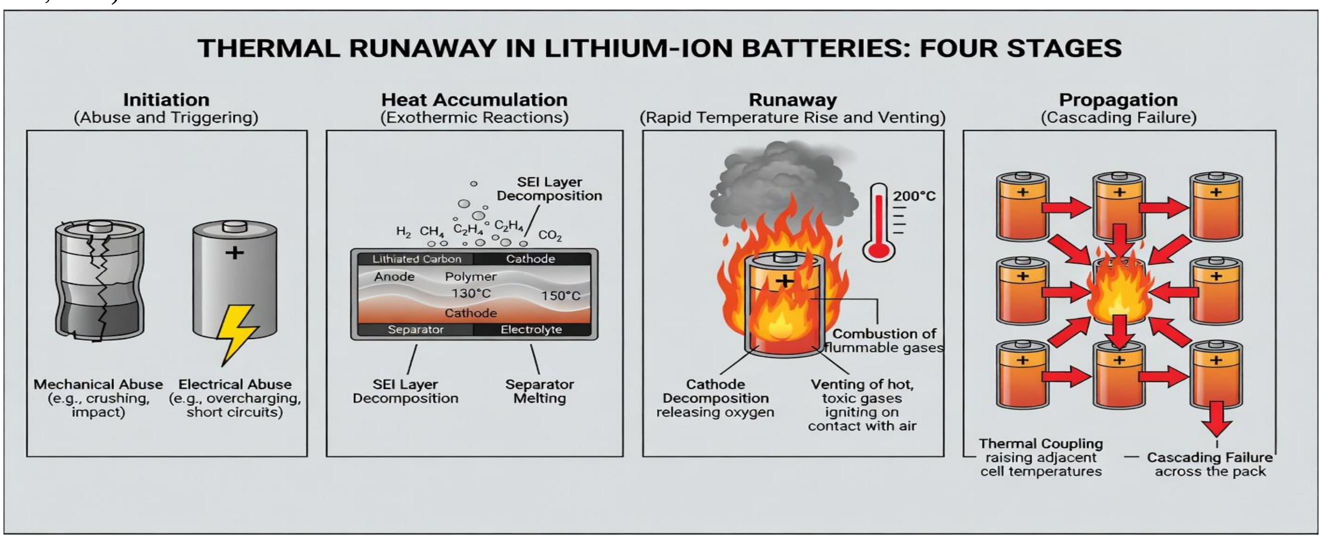
The mechanism of thermal runaway is very complicated and encompasses the coupled effect of electrochemical, thermal, mechanical and chemical. Ren et al. (2021) demonstrated that exothermic reactions between the anode and electrolyte can dominate thermal runaway initiation under certain conditions, challenging the conventional assumption that internal short circuits alone are responsible for catastrophic failure initiation. Similarly, Mao et al. (2020) highlighted the importance of self-heating kinetics and thermal criticality in determining battery safety boundaries.

The hazards associated with thermal runaway extend beyond localized cell failure. Ribière et al. (2012) showed that lithium-ion battery thermal runaway can release substantial quantities of heat and toxic gases, including hydrogen fluoride, thereby creating significant fire and explosion hazards. Wang et al. (2022) further demonstrated that vent gas combustion characteristics vary significantly with battery chemistry and operating conditions.

To improve battery safety, extensive research efforts have focused on the development of early-warning technologies capable of detecting hazardous conditions before catastrophic failure occurs. Conventional battery management systems primarily rely on voltage and temperature monitoring; however, these approaches frequently suffer from delayed response because surface measurements do not adequately represent internal battery conditions (Anthony et al., 2017; Xu et al., 2020).

Consequently, significant attention has shifted toward advanced sensing technologies, including gas sensing, embedded temperature sensing, strain monitoring, force-based diagnostics, and fiber-optic sensing (Fernandes et al., 2018; Cai et al., 2019; Yang et al., 2013; Zhang et al., 2023). In parallel, artificial intelligence and machine learning have emerged as powerful tools for battery prognostics and fault diagnosis. Recent developments include deep learning frameworks, hybrid AI–physics models, transfer learning, digital twins, and state-of-safety prognostic methodologies (Tran and Fowler, 2020; Chen et al., 2024; Jeong et al., 2024; Gu et al., 2025).



Although several recent reviews have addressed thermal runaway warning technologies or machine-learning-based battery prognostics individually, an integrated review combining sensing technologies, intelligent prognostics, physics-informed modeling, and digital twin architectures remains limited. Therefore, this review provides a comprehensive and technically detailed analysis of modern early-warning and prognostic safety frameworks for lithium-ion battery systems.

The main objectives of the Review:

1) To critically analyze the fundamental mechanisms and triggering pathways of thermal runaway in lithium-ion battery systems under thermal, electrical, and mechanical abuse conditions, including self-heating reactions, internal short circuits, gas evolution, and propagation behavior.
2) To systematically review existing early thermal runaway detection and warning techniques based on voltage, current, temperature, gas evolution, swelling, strain, pressure, embedded sensing, and multimodal sensor fusion approaches for electric vehicle battery applications.
3) To evaluate recent advances in artificial intelligence, machine learning, and physics-informed prognostic frameworks for lithium-ion battery safety management, including deep learning, hybrid AI–physics models, transfer learning, few-shot learning, and digital twin-based diagnostics.

4) To examine the development of intelligent battery safety ecosystems and advanced battery management architectures, including IoT-enabled monitoring systems, cloud-edge battery management frameworks, smart thermal management systems, and autonomous safety control strategies.
5) To identify current challenges, research gaps, and future directions associated with reliable thermal runaway prognostics, uncertainty-aware diagnostics, explainable artificial intelligence, embedded sensing technologies, and next-generation intelligent battery safety systems for electric vehicles and energy storage applications.

II. FUNDAMENTALS OF THERMAL RUNAWAY IN LITHIUM-ION BATTERIES

A. *Thermal Runaway Mechanisms:*

Thermal runaway in lithium-ion batteries is a multistage and highly nonlinear process involving coupled electrochemical and thermal reactions. Feng et al. (2018) described thermal runaway as a progressive chain reaction initiated by internal heat accumulation, followed by decomposition of the solid electrolyte interphase (SEI), separator shrinkage, electrolyte decomposition, cathode decomposition, oxygen release, and eventual combustion.

Maleki et al. (1999) investigated the thermal stability of lithium-ion battery components and demonstrated that separators, electrolytes, and electrode materials possess distinct thermal decomposition characteristics. Their work established the foundation for understanding component-level thermal instability.

The thermal runaway process generally begins when internal heat generation exceeds the battery's heat dissipation capability. Mao et al. (2020) investigated self-heating reactions and thermal criticality using accelerating rate calorimetry and emphasized the importance of self-accelerating decomposition temperature (SADT) in determining battery safety limits.

Ren et al. (2021) later refined the understanding of thermal runaway initiation by demonstrating that exothermic reactions between the anode and electrolyte may dominate failure initiation rather than the internal short circuit itself. This finding significantly changed the conventional interpretation of thermal runaway triggering mechanisms.

B. Abuse Conditions and Failure Triggers

Thermal runaway may be triggered by thermal, electrical, or mechanical abuse conditions. Thermal abuse commonly occurs when batteries are exposed to excessive environmental temperatures or localized heating. Zhang et al. (2021) investigated the influence of different heating methods on thermal runaway behavior and demonstrated that heating configuration significantly affects gas evolution and thermal response.

Electrical abuse typically includes overcharging and over-discharging conditions. Zhao et al. (2021) showed that overcharged batteries may exhibit distinct voltage-drop and pressure-evolution characteristics prior to thermal runaway. Liu et al. (2022) further demonstrated that even slight overcharging can induce abnormal heat generation and lithium plating.

Mechanical abuse conditions include crush loading, nail penetration, and impact deformation. Lamb and Orendorff (2014) evaluated different mechanical abuse methodologies and highlighted the critical role of internal short-circuit formation during severe deformation.

C. Thermal Runaway Propagation and Fire Hazards

Thermal runaway propagation represents one of the most severe hazards associated with large-scale battery systems. Once a single cell enters thermal runaway, neighboring cells may experience elevated temperatures, ultimately leading to cascading propagation.

Ribière et al. (2012) investigated fire-induced hazards associated with lithium-ion batteries and demonstrated that thermal runaway events can release substantial heat and toxic gases. Chen et al. (2020) further investigated thermal runaway characteristics of high-energy cylindrical cells and observed violent jet fire behavior and rapid heat release.

Wang et al. (2022) later investigated vent gas explosion characteristics and showed that explosion severity strongly depends on battery chemistry and vent gas composition. Choi et al. (2025) expanded these investigations to large-format battery systems and demonstrated the importance of gas evolution and suppression strategies during pack-level thermal runaway propagation.

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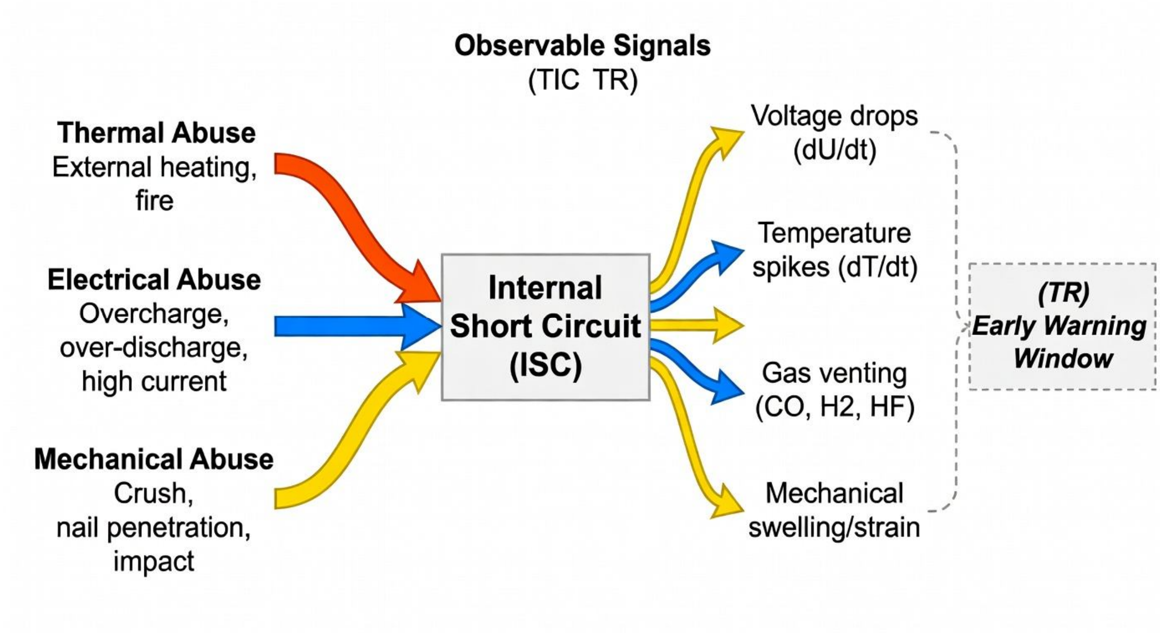

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III. EARLY THERMAL RUNAWAY WARNING SIGNALS AND SENSING TECHNOLOGIES

A. Voltage, Current, and Temperature-Based Warning Signals

Voltage, current, and surface temperature monitoring remain the most widely implemented safety-monitoring approaches in commercial battery management systems. However, several studies have shown that these parameters often provide limited warning time before catastrophic failure.

Anthony et al. (2017) demonstrated that surface temperature measurements frequently fail to accurately represent internal thermal conditions because significant thermal gradients develop inside lithium-ion cells. Xu et al. (2020) further showed that internal temperatures during thermal runaway can greatly exceed externally measured temperatures.

Zhao et al. (2021) reported that voltage-drop behavior during overcharge conditions may provide useful warning information prior to catastrophic failure. Similarly, Liu et al. (2022) demonstrated that abnormal heat generation during constant-voltage charging can act as an early diagnostic indicator.

Despite their widespread implementation, conventional voltage and temperature monitoring strategies frequently suffer from delayed response because internal electrochemical degradation may already be well advanced before measurable external thermal changes occur.

B. Embedded and Internal Temperature Sensing

To overcome the limitations of external sensing approaches, recent research has increasingly focused on embedded and internal sensing technologies. Wei et al. (2021) proposed advanced smart battery architectures integrating embedded multidimensional sensing systems capable of simultaneously monitoring electrochemical, thermal, and mechanical battery states.

Zhang et al. (2023) developed a flexible embedded temperature sensor array capable of detecting hazardous thermal conditions near the onset of SEI decomposition. Their work demonstrated that embedded sensing technologies can provide substantially earlier warning compared with conventional surface-mounted sensors.

Li et al. (2013) investigated temporal and spatial internal temperature variations using embedded thermocouples and reported significant thermal gradients inside lithium-ion cells.

C. Gas-Based Thermal Runaway Warning

Gas evolution has emerged as one of the most promising approaches for early thermal runaway detection because characteristic gases are often released before rapid temperature escalation occurs.

Fernandes et al. (2018) identified and quantified gases released during overcharge conditions using gas chromatography and Fourier-transform infrared spectroscopy. Their work demonstrated that gas evolution can provide valuable information regarding battery degradation and thermal instability.

Pu et al. (2024) combined electronic nose technology with machine-learning algorithms for thermal runaway warning. Their framework utilized MOS gas sensors together with multilayer perceptron, support vector machine, and extreme learning machine algorithms to classify characteristic gases associated with thermal runaway progression highlighted the value of gas-based early-warning systems for pack-level safety management.

D. Swelling, Strain, and Force-Based Diagnostics

Mechanical deformation and swelling behavior are increasingly recognized as valuable early-warning indicators. Cai et al. (2019) modeled battery temperature and expansion force evolution during early thermal runaway and demonstrated that expansion force can rise before significant temperature increase occurs.

Bang et al. (2025) developed a swelling-based thermal runaway detection framework using piezoresistive sponge sensors and demonstrated module-level thermal runaway warning capability more than one thousand seconds before catastrophic failure. Gu et al. (2025) proposed a multidimensional state-of-safety framework integrating strain, temperature, voltage, capacity, and power indicators into a unified safety metric capable of providing extended warning horizons.

E. Fiber-Optic and Embedded Smart Sensing

Fiber-optic sensing technologies have attracted considerable interest because of their high sensitivity and distributed sensing capability. Yang et al. (2013) demonstrated real-time temperature monitoring using fiber Bragg grating sensors. Nascimento et al. (2019) later expanded this concept by implementing distributed thermal mapping systems capable of monitoring spatial temperature distributions under varying operating conditions.

Recent advances in embedded sensing technologies have accelerated the development of smart battery architectures capable of supporting intelligent battery management systems.

Table 1: Embedded and Internal Sensing Technologies for Early Thermal Runaway Detection

Author & year	Sensor Technology	Measured Parameter	Major Findings	Practical Significance
Anthony et al. (2017)	Non-invasive thermal estimation	Internal temperature	Surface temperature did not accurately represent internal thermal conditions	Highlighted limitations of external sensing
Li et al. (2013)	Embedded thermocouples	Internal thermal gradients	Significant spatial and temporal internal temperature variation observed	Demonstrated hotspot formation inside cells
Xu et al. (2020)	Internal thermocouple	Core temperature during TR	Internal temperatures greatly exceeded external temperatures	Improved understanding of TR evolution

	sensing		during TR	
Yang et al. (2013)	Fiber Bragg grating (FBG) sensors	Real-time temperature	Demonstrated real-time optical temperature monitoring capability	High sensitivity and EMI immunity
Nascimento et al. (2019)	Distributed fiber sensing	Spatial thermal mapping	Enabled distributed thermal monitoring under varying operating conditions	Useful for pack-level thermal mapping
Zhang et al. (2023)	Flexible embedded PTCR sensor array	Internal temperature near SEI decomposition	Embedded sensors detected hazardous conditions near SEI decomposition onset (~67 °C)	Earlier warning than surface-mounted sensors
Mei et al. (2023)	Lab-on-fiber operando sensing	Internal electro-thermal behavior	Enabled operando monitoring of battery internal conditions	Advanced next-generation sensing approach
Wei et al. (2021)	Embedded multidimensional sensing architecture	Thermal, electrochemical, mechanical states	Proposed smart battery framework integrating embedded sensing	Foundation for intelligent BMS and digital twins

Table 2: Comparison of Gas-Based Thermal Runaway Detection Methods

Author & year	Detection Technique	Target Gas/Signal	Key Findings	Advantages	Limitations
Fernandes et al. (2018)	FTIR + GC-MS gas analysis	CO_2, CO, hydrocarbons, vent gases	Gas evolution begins before catastrophic thermal escalation during overcharge abuse	High chemical specificity	Complex instrumentation
Song et al. (2025)	Gas sensor-based warning framework	H_2, CO, VOCs	Gas sensing provides rapid TR warning capability and strong sensitivity to early electrochemical degradation	Fast response and practical integration	Sensor cross-sensitivity
Pu et al. (2024)	Electronic nose + ML algorithms	VOC mixtures	MLP, SVM, and ELM models improved TR identification accuracy; gas sensing detected failure earlier than voltage/temperature monitoring	Early-stage warning capability	Environmental sensitivity
Wang et al. (2022)	Vent gas explosion characterization	Combustible vent gases	Explosion severity strongly depended on vent gas composition and battery chemistry	Important for ESS safety assessment	Requires controlled safety testing
Choi et al. (2025)	Pack-level vent gas monitoring	VOC concentration and vent gases	Vent gas monitoring enabled early detection in 7.5 kWh module and 74 kWh pack experiments	Practical large-scale applicability	Complex pack-level gas flow behavior

IV. ARTIFICIAL INTELLIGENCE AND PROGNOSTIC SAFETY FRAMEWORKS

A. Machine Learning-Based Fault Diagnosis

Machine learning has emerged as one of the most important enabling technologies for modern battery prognostics and health management. Tran and Fowler (2020) reviewed lithium-ion battery fault diagnostic algorithms and categorized existing approaches into model-based, signal-based, and knowledge-based frameworks.

Li et al. (2023) comprehensively reviewed machine-learning-assisted battery thermal management systems and discussed the application of artificial neural networks, convolutional neural networks, long short-term memory networks, and reinforcement learning algorithms for battery thermal safety management.

Machine-learning approaches are particularly attractive because they can capture highly nonlinear relationships among battery operating variables without requiring fully detailed electrochemical models.

B. Deep Learning-Based Thermal Runaway Prediction

Deep learning approaches have demonstrated strong capability for modeling complex temporal and spatial battery behavior. Chen et al. (2024) proposed a data-driven thermal runaway warning framework for retired lithium-ion batteries using Bi-LSTM networks, attention mechanisms, and ensemble learning.

Cheng et al. (2025) developed an LSTM-TCN hybrid framework for charging-network-based thermal runaway warning using residual-based monitoring techniques.

Athanasopoulos et al. (2025) investigated thermal runaway detection using multimodal thermal and optical imaging combined with convolutional neural networks and vision transformers.

C. Hybrid AI–Physics Frameworks

Purely data-driven models often suffer from limited interpretability and reduced generalization capability under unseen operating conditions. Chen et al. (2024) proposed a hybrid AI–physics thermal runaway warning framework combining K-means anomaly detection with electrochemical thermal modeling. Their approach achieved improved prediction accuracy while reducing false alarms.

Zhang et al. (2020) developed computational safety-regime models capable of identifying critical operating regions associated with internal short-circuit-triggered thermal runaway.

Hybrid AI–physics approaches are increasingly regarded as one of the most promising directions for future battery prognostics because they combine the predictive capability of machine learning with the physical consistency of electrochemical models.

D. Physics-Informed Deep Learning and Digital Twins

Recent advances in digital twin technology have significantly expanded the scope of intelligent battery safety management. Jeong et al. (2024) proposed a multiphysics-informed DeepONet framework capable of predicting internal battery temperature distributions at substantially lower computational cost than conventional finite-element simulations.

Digital twins enable real-time synchronization between physical battery systems and virtual computational models, thereby supporting predictive safety assessment, anomaly detection, and adaptive control.

Wei et al. (2021) emphasized the importance of embedded multidimensional sensing systems for enabling future digital twin-based battery architectures.

E. Transfer Learning and Data-Efficient Prognostics

One of the major limitations associated with machine-learning-based battery safety research is the scarcity of high-quality thermal runaway datasets. Masalkovaitė et al. (2024) addressed this challenge using transfer learning approaches combined with the Battery Failure Databank. Their framework predicted thermal runaway heat-release variability using limited calorimetry measurements and simplified experimental features. Few-shot learning and transfer learning approaches are expected to become increasingly important because thermal runaway events are inherently difficult and expensive to reproduce experimentally.

F. State-of-Safety Prognostic Frameworks

Conventional battery safety systems generally rely on binary threshold-based protection strategies. However, recent research has shifted toward continuous prognostic safety assessment. Gu et al. (2025) proposed a multidimensional state-of-safety framework incorporating strain, temperature, voltage, capacity, and power indicators into a unified safety metric. Their framework demonstrated significantly extended warning horizons compared with conventional threshold-based approaches.

The transition from passive protection toward prognostic safety assessment represents a major paradigm shift in modern battery management system design.

Table 3: AI and Machine Learning Approaches for Thermal Runaway Prognostics

Author & year	AI/ML Technique	Input Features	Major Contribution	Key Advantage
Tran and Fowler (2020)	Fault diagnostic algorithm taxonomy	Voltage, current, thermal data	Classified model-based, signal-based, and knowledge-based diagnosis methods	Structured framework for intelligent diagnostics

Li et al. (2023)	ANN, CNN, LSTM, DRL	Battery thermal and operational parameters	Reviewed ML-assisted BTMS and intelligent thermal management	Broad AI integration for battery safety
Chen et al. (2024)	Bi-LSTM + attention + ensemble learning	Battery operational data	Developed data-driven TR warning for retired batteries	Addressed limited-data conditions
Cheng et al. (2025)	LSTM-TCN hybrid model	Charging-network operational data	Residual-based TR warning during charging	Suitable for fleet-scale charging safety
Athanasopoulos et al. (2025)	CNN + Vision Transformer	Thermal and optical images	Multimodal TR detection using deep learning	Advanced image-based diagnostics
Chen et al. (2024)	Hybrid AI–physics framework	Thermal/electrochemical data	Combined K-means anomaly detection with physics modeling	Reduced false alarms
Jeong et al. (2024)	Physics-informed DeepONet	Virtual multiphysics thermal data	Predicted internal temperature fields with much lower computational cost than FEM	Strong digital twin potential
Masalkovaitė et al. (2024)	Transfer learning + few-shot learning	Battery Failure Databank + calorimetry data	Predicted TR heat-release variability with limited data	Data-efficient prognostics
Gu et al. (2025)	State-of-Safety (SOS) framework	Strain, voltage, temperature, power, capacity	Introduced multidimensional safety metric with extended warning horizon	Continuous prognostic safety assessment
Zhao et al. (2024)	ML prognostic review framework	Multi-source battery datasets	Reviewed supervised, reinforcement, self-supervised, and physics-informed learning approaches	Comprehensive future-oriented AI roadmap

V. SMART BATTERY SAFETY ECOSYSTEMS

A. *Smart Batteries and Intelligent Battery Management Systems:*

Future battery systems are increasingly expected to incorporate embedded intelligence, distributed sensing, adaptive control, and autonomous safety management capability. Wei et al. (2021) proposed advanced smart battery architectures integrating embedded multidimensional sensing systems capable of monitoring electrochemical, thermal, and mechanical states simultaneously.

Hu et al. (2024) reviewed thermal runaway warning technologies and emphasized the growing importance of intelligent battery management systems capable of integrating sensing, diagnostics, and prognostics into unified safety frameworks.

B. *IoT and Cloud-Based Battery Monitoring:*

IoT-enabled battery monitoring systems are becoming increasingly important for electric vehicles and energy storage systems. Krishna et al. (2024) proposed an IoT-based battery monitoring system for electric vehicles capable of remote battery-state monitoring. Wang et al. (2023) later developed an NB-IoT–ZigBee battery monitoring framework integrating distributed sensing with cloud communication. Chen et al. (2024) further proposed a cloud–network–edge–end online battery monitoring architecture for intelligent battery maintenance and fault diagnosis.

C. *Thermal Runaway Suppression and Mitigation*

In addition to early-warning technologies, thermal runaway suppression and propagation mitigation strategies are essential for large-scale battery systems. Choi et al. (2025) investigated thermal runaway suppression in large-format lithium-ion battery systems using direct water injection and carbon dioxide cooling approaches.

Mahdy et al. (2025) evaluated thermal runaway propagation behavior under different heating conditions and demonstrated that heating location significantly affects propagation severity.

VI. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite substantial progress in thermal runaway detection and prognostic safety management, several important challenges remain.

1) One major challenge involves the scarcity of high-quality thermal runaway datasets required for machine-learning model training. Thermal runaway events are expensive and hazardous to reproduce experimentally, limiting the availability of robust datasets.
2) Another critical challenge involves the reliability and robustness of sensing systems under real-world operating conditions. Gas sensors, embedded sensors, and strain-monitoring systems may experience drift, environmental interference, or degradation during long-term operation.
3) The interpretability and generalization capability of machine-learning models also remain important concerns. Although deep learning frameworks can achieve high prediction accuracy, purely data-driven approaches often lack physical interpretability.
4) Future battery safety systems are expected to increasingly incorporate hybrid AI–physics frameworks, uncertainty-aware prognostics, transfer learning, and digital twin architectures. Physics-informed machine learning, embedded multidimensional sensing, and state-of-safety methodologies are expected to play a major role in next-generation intelligent battery management systems.
5) The integration of cloud computing, edge intelligence, IoT communication, and autonomous safety control may ultimately enable self-adaptive battery safety ecosystems capable of predicting hazardous conditions long before catastrophic failure occurs.

VII. CONCLUSIONS

The main conclusions of this extensive review are as listed below:

1) Thermal runaway remains one of the most critical safety challenges associated with lithium-ion battery systems. Conventional threshold-based protection strategies are increasingly insufficient for modern high-energy battery applications because they frequently provide limited warning time before catastrophic failure.
2) Recent advances in sensing technologies, machine learning, hybrid AI–physics frameworks, and digital twin architectures have significantly improved the capability for early thermal runaway detection and prognostic safety assessment.
3) Gas sensing, swelling diagnostics, embedded sensing, and multimodal sensor fusion have demonstrated strong potential for improving early-warning reliability. Simultaneously, machine-learning and deep-learning frameworks are transforming battery safety diagnostics by enabling predictive and adaptive safety management.
4) Future battery safety systems are expected to progressively transition toward intelligent, autonomous, and prognostic safety ecosystems integrating embedded multidimensional sensing, physics-informed artificial intelligence, digital twins, and cloud-edge battery management frameworks.
5) The continued development of reliable, interpretable, and scalable prognostic safety systems will be essential for ensuring the safe large-scale deployment of electric vehicles and next-generation energy storage technologies.

REFERENCES

[1] Jingyuan Zhao, Xuning Feng, Quanquan Pang, Michael Fowler, Yubo Lian, Minggao Ouyang, Andrew F. Burke, "Battery safety: Machine learning-based prognostics", Progress in Energy and Combustion Science, Volume 102, 2024, 101142, ISSN 0360-1285, https://doi.org/10.1016/j.pecs.2023.101142.

[2] Xuning Feng, Minggao Ouyang, Xiang Liu, Languang Lu, Yong Xia, Xiangming He, "Thermal runaway mechanism of lithium ion battery for electric vehicles: A review", Energy Storage Materials, Volume 10, 2018, Pages 246-267, ISSN 2405-8297, https://doi.org/10.1016/j.ensm.2017.05.013.

[3] Huaibin Wang, Hui Xu, Zelin Zhang, Qinzheng Wang, Changyong Jin, Changjun Wu, Chengshan Xu, Jinyuan Hao, Lei Sun, Zhiming Du, Yang Li, Junli Sun, Xuning Feng, "Fire and explosion characteristics of vent gas from lithium-ion batteries after thermal runaway: A comparative study", eTransportation, Volume 13, 2022, 100190, ISSN 2590-1168, https://doi.org/10.1016/j.etran.2022.100190.

[4] Dongsheng Ren, Xuning Feng, Lishuo Liu, Hungjen Hsu, Languang Lu, Li Wang, Xiangming He, Minggao Ouyang, "Investigating the relationship between internal short circuit and thermal runaway of lithium-ion batteries under thermal abuse condition", Energy Storage Materials, Volume 34, 2021, Pages 563-573, ISSN 2405-8297, https://doi.org/10.1016/j.ensm.2020.10.020.

[5] Binbin Mao, Peifeng Huang, Haodong Chen, Qingsong Wang, Jinhua Sun, "Self-heating reaction and thermal runaway criticality of the lithium ion battery", International Journal of Heat and Mass Transfer, Volume 149, 2020, 119178, ISSN 0017-9310, https://doi.org/10.1016/j.ijheatmasstransfer.2019.119178..

[6] Perrine Ribiere, Sylvie Grugeon, Mathieu Morcrette, Simeon Boyanov, Stephane Laruellea, "Investigation on the fire-induced hazards of Li-ion battery cells by fire calorimetry", Energy Environ. Sci., 2012, 5, 5271, DOI: 10.1039/c1ee02218k

[7] Dean Anthony, Derek Wong, David Wetz, Ankur Jain, "Non-invasive measurement of internal temperature of a cylindrical Li-ion cell during high-rate discharge", International Journal of Heat and Mass Transfer, Volume 111, 2017, Pages 223-231, ISSN 0017-9310, https://doi.org/10.1016/j.ijheatmasstransfer.2017.03.095.

[8] Chengshan Xu, Xuning Feng, Wensheng Huang, Yongkang Duan, Tianyu Chen, Shang Gao, Languang Lu, Fachao Jiang, Minggao Ouyang, "Internal temperature detection of thermal runaway in lithium-ion cells tested by extended-volume accelerating rate calorimetry", Journal of Energy Storage, Volume 31, 2020, 101670, ISSN 2352-152X, https://doi.org/10.1016/j.est.2020.101670.

[9] Y. Fernandes, A. Bry, S. de Persis, "Identification and quantification of gases emitted during abuse tests by overcharge of a commercial Li-ion battery", Journal of Power Sources, Volume 389, 2018, Pages 106-119, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2018.03.034.

[10] Ting Cai, z Anna G. Stefanopoulou and Jason B. Siegel, "Modeling Li-Ion Battery Temperature and Expansion Force during the Early Stages of Thermal Runaway Triggered by Internal Shorts" , Journal of The Electrochemical Society, 166 (12) A2431-A2443 (2019).

[11] Gang Yang, Catia Leitão, Yuhong Li, João Pinto, Xuefan Jiang, "Real-time temperature measurement with fiber Bragg sensors in lithium batteries for safety usage, Measurement", Volume 46, Issue 9, 2013, Pages 3166-3172, ISSN 0263-2241, https://doi.org/10.1016/j.measurement.2013.05.027.

[12] Hengyi Zhang, Xiaoshan Zhang, Wenwu Wang and Ping Yu, "Detection and Prediction of the Early Thermal Runaway and Control of the Li-Ion Battery by the Embedded Temperature Sensor Array," Sensors 2023, 23, 5049, https://doi.org/10.3390/s23115049.

[13] Manh-Kien Tran and Michael Fowler, "A Review of Lithium-Ion Battery Fault Diagnostic Algorithms: Current Progress and Future Challenges" Algorithms 2020, 13, 62; doi:10.3390/a13030062.

[14] Chen, Q.; He, Y.; Fang, N.;Yu, G. "A Combined Data-Driven and Model-Based Algorithm for Accurate Battery Thermal Runaway Warning." Sensors 2024, 24, 4964. https://doi.org/10.3390/s24154964.

[15] Jinho Jeong, Eunji Kwak, Jun-hyeong Kim, Ki-Yong Oh, "Prediction of thermal runaway for a lithium-ion battery through multiphysics-informed DeepONet with virtual data", eTransportation, Volume 21, 2024, 100337, ISSN 2590-1168, https://doi.org/10.1016/j.etran.2024.100337.

[16] Gu, X., Shang, Y., Li, J. et al. Early warning of thermal runaway based on state of safety for lithium-ion batteries. Commun Eng 4, 106 (2025). https://doi.org/10.1038/s44172-025-00442-1.

[17] Xuning Feng, Minggao Ouyang, Xiang Liu, Languang Lu, Yong Xia, Xiangming He, Thermal runaway mechanism of lithium ion battery for electric vehicles: A review, Energy Storage Materials, Volume 10, 2018, Pages 246-267, ISSN 2405-8297, https://doi.org/10.1016/j.ensm.2017.05.013.

[18] Hossein Maleki, Guoping Deng,* Anaba Anani, and Jason Howard, Thermal Stability Studies of Li-Ion Cells and Components, Journal of The Electrochemical Society, 146 (9) 3224-3229 (1999).

[19] Qingsong Zhang, Tiantian Liu, Qiong Wang, Experimental study on the influence of different heating methods on thermal runaway of lithium-ion battery, Journal of Energy Storage, Volume 42, 2021, 103063, ISSN 2352-152X, https://doi.org/10.1016/j.est.2021.103063.

[20] Chunpeng Zhao, Tinghua Wang, Zheng Huang, Jingyun Wu, Hongwei Zhou, Mina Ma, Jiajia Xu, Zhaoyu Wang, Huang Li, Jinhua Sun, Qingsong Wang, Experimental study on thermal runaway of fully charged and overcharged lithium-ion batteries under adiabatic and side-heating test, Journal of Energy Storage, Volume 38, 2021, 102519, ISSN 2352-152X, https://doi.org/10.1016/j.est.2021.102519.

[21] Jialong Liu, Zonghou Huang, Jinhua Sun, Qingsong Wang, Heat generation and thermal runaway of lithium-ion battery induced by slight overcharging cycling, Journal of Power Sources, Volume 526, 2022, 231136, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2022.231136.

[22] Joshua Lamb, Christopher J. Orendorff, Evaluation of mechanical abuse techniques in lithium ion batteries, Journal of Power Sources, Volume 247, 2014, Pages 189-196, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2013.08.066.

[23] Haodong Chen, Jonathan E.H. Buston, Jason Gill, Daniel Howard, Rhiannon C.E. Williams, Chandra M. Rao Vendra, Ashish Shelke, Jennifer X. Wen, An experimental study on thermal runaway characteristics of lithium-ion batteries with high specific energy and prediction of heat release rate, Journal of Power Sources, Volume 472, 2020, 228585, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2020.228585.

[24] Choi, S.; Lee, K.; Kim, J.; Oh, S.; Joo, J.; Bae, E.; Lee, H.; Kim, M. Early Detection and Suppression of Thermal Runaway in Large-Format Lithium-Ion Batteries: Insights from Experimental Analysis. Energies 2025, 18, 155. https://doi.org/10.3390/en18010155.

[25] Zhongbao Wei, Jiyun Zhao, Hongwen He, Guanglin Ding, Haoyong Cui, Longcheng Liu, Future smart battery and management: Advanced sensing from external to embedded multi-dimensional measurement, Journal of Power Sources, Volume 489, 2021, 229462, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2021.229462.

[26] Zhang X, Chen S, Zhu J, Gao Y. A Critical Review of Thermal Runaway Prediction and EarlyWarning Methods for Lithium-Ion Batteries. Energy Mater. Adv. 2023;4:Article 0008. https://doi. org/10.34133/energymatadv.0008.

[27] Zhe Li, Jianbo Zhang, Bin Wu, Jun Huang, Zhihua Nie, Ying Sun, Fuqiang An, Ningning Wu, Examining temporal and spatial variations of internal temperature in large-format laminated battery with embedded thermocouples, Journal of Power Sources, Volume 241, 2013, Pages 536-553, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2013.04.117.

[28] Pu, Z.; Yang, M.; Jiao, M.; Zhao, D.; Huo, Y.;Wang, Z. Thermal RunawayWarning of Lithium Battery Based on Electronic Nose and Machine Learning Algorithms. Batteries 2024, 10, 390. https://doi.org/10.3390/batteries10110390.

[29] Joohyung Bang, Byungkwon Chun, Minhyeok Kim, Jaeyoung Lim, Yongha Han, Hongyun So, Rapid thermal runaway detection of lithium-ion battery via swelling-based state-of-charge monitoring using piezoresistive sponge sensor, eTransportation, Volume 24, 2025, 100404, ISSN 2590-1168, https://doi.org/10.1016/j.etran.2025.100404.

[30] Micael Nascimento, Marta S. Ferreira, João L. Pinto, Temperature fiber sensing of Li-ion batteries under different environmental and operating conditions, Applied Thermal Engineering, Volume 149, 2019, Pages 1236-1243, ISSN 1359-4311, https://doi.org/10.1016/j.applthermaleng.2018.12.135.

[31] Ao Li, Jingwen Weng, Anthony Chun Yin Yuen, Wei Wang, Hengrui Liu, Eric Wai Ming Lee, Jian Wang, Sanghoon Kook, Guan Heng Yeoh, Machine learning assisted advanced battery thermal management system: A state-of-the-art review, Journal of Energy Storage, Volume 60, 2023, 106688, ISSN 2352-152X, https://doi.org/10.1016/j.est.2023.106688.

[32] Chen K, Luo L, Lei W, Lv P and Zhang L (2024) Design and implementation of online battery monitoring and management system based on the internet of things. Front. Energy Res. 12:1454398. doi: 10.3389/fenrg.2024.1454398.

[33] Cheng, YM., Gao, DX., Zhao, FM. *et al.* Early warning method for charging thermal runaway of electric vehicle lithium-ion battery based on charging network. *Sci Rep* 15, 7895 (2025). https://doi.org/10.1038/s41598-025-92738-7.

[34] A. Athanasopoulos, M. Mihal´ak and M. Pietrasik,"Deep Learning Methods for Detecting Thermal Runaway Events in Battery Production Lines," 2025 IEEE 8th International Conference on Industrial Cyber-Physical Systems (ICPS), Emden, Germany, 2025, pp. 1-6, doi: 10.1109/ICPS65515.2025.11087884.

[35] Liwen Zhang, Peng Zhao, Meng Xu, Xia Wang, Computational identification of the safety regime of Li-ion battery thermal runaway, Applied Energy, Volume 261, 2020, 114440, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2019.114440.

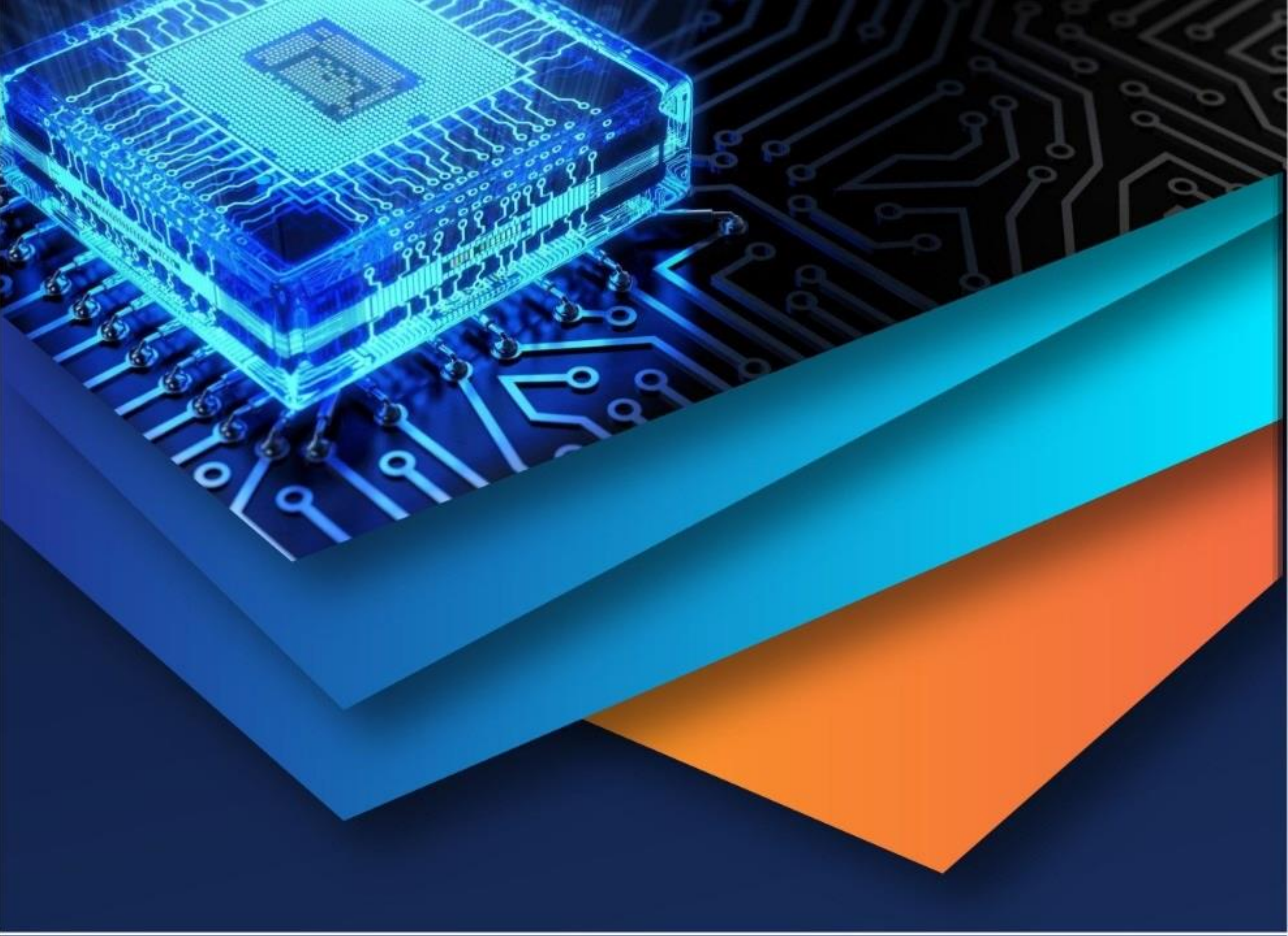
[36] Masalkovaitė, K., Gasper, P. & Finegan, D.P. Predicting the heat release variability of Li-ion cells under thermal runaway with few or no calorimetry data. *Nat Commun* 15, 8399 (2024). https://doi.org/10.1038/s41467-024-52653-3.

[37] Dunan Hu, Sheng Huang, Zhen Wen, Xiuquan Gu, Jianguo Lu, A review on thermal runaway warning technology for lithium-ion batteries, Renewable and Sustainable Energy Reviews, 2024, 114882, ISSN 1364-0321, https://doi.org/10.1016/j.rser.2024.114882.

[38] G. Krishna, R. Singh, A. Gehlot, V. A. Shaik, B. Twala, and N. Priyadarshi, "IoT-based real-time analysis of battery management system with long range communication and FLoRa," *Results in Engineering*, vol. 23, pp. 102770, 2024, doi: 10.1016/j.rineng.2024.102770.

[39] Wang, L.;Wang, C.; Lu, X.; Ping, D.; Jiang, S.;Wang, X.; Zhang, J. A Design for a Lithium-Ion Battery Pack Monitoring System Based on NB-IoT-ZigBee. Electronics **2023**, 12, 3561. https://doi.org/10.3390/electronics12173561.

[40] Mahdy, O.S., Ali, A.B.M., Mostafa, L. *et al.* Quantitative evaluation of thermal runaway in lithium-ion batteries under critical heating conditions to enhance safety. *Sci Rep* **15**, 24004 (2025). https://doi.org/10.1038/s41598-025-07824-7.



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