EPJ Web of Conferences **355**, 01010 (2026) https://doi.org/10.1051/epjconf/202635501010
STAAAR 2025

An intelligent hybrid framework for lithium-ion battery fault diagnostics using unsupervised learning and heuristic integration

M.Arulmozhi[1*], *U.*Jaykrithy[2], V.Kavishree[2], and C.*Amutha*[3]

[1,3]Assistant Professor (SG), Department of EEE, Rajalakshmi engineering college, Chennai, India
[2] UG Scholar, Department of EEE, Rajalakshmi engineering college, Chennai, India

Abstract. Lithium-ion batteries play a crucial role in electric vehicles, renewable energy systems, and portable electronics because of their high energy density and long cycle life. However, challenges like overcharging, overheating, internal short circuits, and gradual degradation can lower performance, reduce lifespan, and create safety risks. The early fault detection through continuous monitoring is essential to address these safety concerns, This study presents a framework that uses sensor measurements such as voltage, current, temperature, and state of charge to assess the health of lithium batteries. The method combines an unsupervised learning algorithm, Isolation Forest, with a heuristic fault analysis approach to spot unusual behavior and classify the states as normal or faulty. Experimental investigations identified fifteen different fault occurrences, including internal short circuits and thermal issues. Correlation assessments show that the framework effectively detects sudden faults. The system enhances safety and reliability by identifying faults early. With an accuracy of about 90 to 95%, it demonstrates significant potential for real-time battery health monitoring.

1 Introduction

In recent years, the topic of fault detection in lithium, ion (Li, ion) batteries has become very popular because of the rise of electric vehicles (EVs) and the crucial safety issues that come with sudden failures. Simply checking the voltage or temperature against preset static thresholds cannot always solve the problem since such methods do not really consider the complex and ever, changing behaviour of battery systems. Recent research has thus considered various data, driven methods including dynamical deep learning, supervised and unsupervised machine learning, and hybrid techniques to deal with these challenges. Deep learning frameworks will predict time variant battery parameters like voltage, current, state of charge (SOC), and temperature. By uncovering hidden nonlinear correlations over multi, dimensional signals, these models are capable of spotting both slow and fast battery anomalies [1]. Nevertheless, the dependence of these approaches on labelled data and their

---

* Corresponding author: arulmozhi.m@rajalakshmi.edu.in

complex nonlinearity hamper their ability to guarantee safety in the actual world. Compared to conventional threshold, based methods, supervised machine learning algorithms have able to better detect internal short circuits (ISCs) and voltage, related faults, particularly under dynamic operating conditions [2]. The very latest in machine learning, especially graph, based neural networks, has demonstrated great ability in reflecting both spatial and labelled fault datasets and struggle to generalize when faced with rare or unseen fault types [3]. To address this limitation, a different approach described in [4] focuses on statistical modeling of battery behavior, specifically for electric scooter battery packs. This method involves learning the distribution of key battery parameters in a cloud-based environment and using metrics like z-scores and quantile thresholds to detect outliers in real time. Since it doesn't require detailed physics-based modeling, it's particularly well-suited for large-scale fleet monitoring, where collecting labelled data can be challenging. The system has shown good performance in identifying recurring and distributional anomalies, and due to its relatively low computational demand, it can be deployed in real-time applications. However, the reliance on fixed statistical rules can lead to false positives especially under non-stationary conditions like fluctuating loads or aging effects and may not be well-suited for identifying more complex, time-evolving faults.

Meanwhile, based on the situation, traditional physics, based methods have generally gone in a different direction. A paper [5] gives a detailed review of fault evolution in automotive lithium, ion batteries through the study of failure propagation along thermal, electrochemical, and mechanical domains. This kind of work is very helpful for Development of safer Battery Management System (BMS) especially under changing operational conditions. Nevertheless, such approaches are generally very expensive as they rely on experimental setups that are not always easy to adapt from one battery system to another. On top of that, these methods are usually not capable of catching faults at the precursor stage, let alone the real, time detection or automation of this process. To solve that problem, a different approach has been suggested, which is based on predicting thermal runaway by using sensor data to allow for fault localization and early detection at a higher precision level [6]. Although the results so far look quite good, machine learning algorithms here still need high, quality, well, rounded datasets as training material. Therefore, these algorithms may not be able to recognize new faults or changes in system configuration very well. According to the latest studies, thermal events such as runaway in lithium, ion batteries are complicated phenomena that can be associated with the interaction of electrochemical, thermal, and mechanical processes, in particular. These studies also reveal that utilizing solely fixed thresholds or supervised fault detection methods can significantly impair the ability to detect early, stage faults of fault development [7–9]. Batteries that are going through an aging process are continuously being studied by checking their slow changes such as capacity fade, increase in internal resistance, and breakdown of electrolyte, which helps in estimating the battery's remaining useful life (RUL) as well as differentiating between slow degradation and sudden fault events [1012]. However, while these methods are very good at figuring out how healthy the battery is over a long period, they generally have a low level of dependability in spotting rare, unobserved anomalies.

To tackle the outlined problems, the authors present a Hybrid structure that mixes unsupervised machine learning, Isolation Forest anomaly detection, and the application of heuristic rules. This solution blends the physics, based heuristic, guided detection with an adaptive unsupervised detection to discover the anomalies that have not been previously recorded. We can identify earlier both faults that are known and those that are novel, and at the same time, improve fault coverage. Therefore, it leads to fewer missed occurrences, and the system can be used to track a variety of operating conditions. In addition, this framework serves as a complement to diagnostics that are based on the aging process. The objectives are listed below

- Detect abnormal patterns in battery time series data through a combination of unsupervised learning and heuristic methods, including scenarios that the conventional rule, based approaches fail to capture.
- Allow early and interpretable fault detection by combining machine learning, based anomaly scores with domain, specific heuristic rules for creating meaningful, timestamp, level fault labels.
- Facilitate diagnostics by aggregating the detected anomalies into events for reporting and integration into battery management systems.

The proposed method is novel in that it can automatically identify the operating limits of a battery from the raw data and then use these limits to adjust the anomaly scores. As a result, it is a more reliable way of detecting faults than the existing methods. The paper is structured as follows: Section 2 outlines the proposed system. Section 3 illustrates the mathematical modelling of the unsupervised anomaly detection technique. Section 4 is a discussion on the findings, scores, and the classification of the four most common faults. Section 5 is the conclusion

2 System Architecture and Diagnostic Flow

The Hybrid Fault Detection Model proposed combines data, driven and physics, based approaches to significantly improve the reliability of fault detection. Fig. 1 gives a schematic depiction of the whole setup. At the beginning, raw sensor data are gathered and automatically paired with the correct physical signals. The resulting sets of signals are then smoothed and differentiated to remove measurement noise and to bring out the transient behaviours that are the first signs of fault. At the same time, a set of rolling statistical features and an internal resistance (IR) proxy are derived to capture the temporal variations and degradation trends in the system.

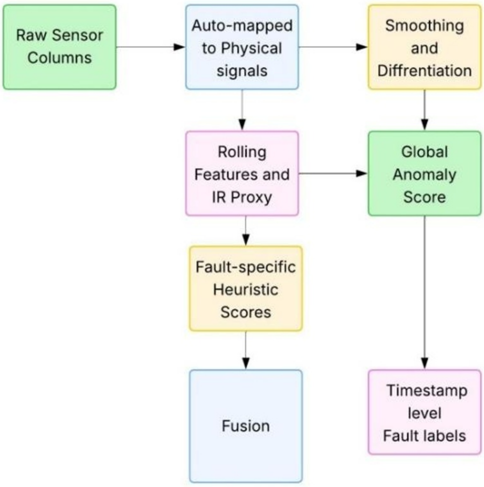

Fig.1. Hybrid Fault detection model

There are two paths through which the processed features are evaluated. A global anomaly score is generated by the first path only, thus it basically quantifies the extent of deviation from the normal behaviour, and it uses statistical and trend, based indicators. On the other hand, the second path produces fault, specific heuristic scores, five of which are basically models derived based on the physical and empirical relationships and represent five different abnormal conditions. Then, global and heuristic indicators are combined to obtain time stamp, level fault labels that both localize and classify the faults accurately. This hybrid method is a perfect mixture of the advantages of the physics, based methods which are understandable and the data, driven methods which are adaptive, thereby a powerful and reliable detection of faults that can be easily explained is available, irrespective of the changing operating conditions.

3 Mathematical model of the Unsupervised–Heuristic Hybrid Approach

One of the ways to get an insight into the battery behaviour and the sensor signal changes over time is through mathematical modelling. This is basically using equations and algorithms to describe the measured signals, time steps, and features of the signal such as gradients, rolling averages, and filtered values, thus making prediction and estimation of battery performance under various operation conditions more accurate and easier. This method helps in identifying faults, and diagnostic indicators by applying statistical and rule-based techniques to time-series data. The equations from (1) to (23) provide insights into fault detection by generating heuristic scores that support the overall analysis

- Let $t € \{1,.....N\}$ represent the discrete sample index.
- Observed signals from the dataset: V(t), I(t), SOC(t), T(t),v(t),m(t). Any column mapped differently is replaced by the corresponding symbol.
- The small numeric stability constant is ε
- Savitzky Golay filter with window *w* and polyorder *p* is represented by $SG(\cdot;w,p)$
- $\nabla x(t)$ is the discrete gradient
- The rolling window aggregate of length w is $r_w(\cdot)$
- $IF(\cdot)$ is the isolation forest decision function output
- The z score normalization is represented as $z(\cdot)$
- $[x]_+ := \max(0,x)$

3.1 Column statistics & heuristic mapping

For each numeric column f in the dataset compute:

$$\min_f = \min_t f(t),\ \max_f = \max_t f(t),\ \mu_c = \frac{1}{N}\sum_{t=1}^{N} f(t),\ \sigma_c = \sqrt{\frac{1}{N}\sum_{t=1}(f(t)-\mu_c)^2} \tag{1}$$

$$\text{Zero fraction: } frac_{f=}\frac{1}{N}\sum_{t=1} 1\{f(t) = 1\} \tag{2}$$

Monotonic fraction

$$frac_{m=}\frac{1}{N}\sum_{t=2}^{N} 1 frac_{f=}\frac{1}{N}\sum_{t=1} 1\{f(t) - f(t-1\} \geq -10^{-6}\} \tag{3}$$

3.2 Heuristic scores

Equations (4) – (10) illustrate the computation of the scoring metrics.

Voltage score:

$$s_f^V = \begin{cases} \frac{1}{\sigma_c} \\ 0\,, otherwise \end{cases}, if\ 0 \le min_f \le max_f \le 500\ and\ 2 \le \mu_c \le 500, \tag{4}$$

Current score:

$$s_f^I = \begin{cases} \sigma_c \\ 0\,, otherwise \end{cases}, if\ min_f < 0\ \ and\ max_f > 0\ and\ \sigma_c > 0, \tag{5}$$

SOC score:

$$s_f^{SOC} = \begin{cases} 100 - |50 - \mu_c| \\ 0, otherwise \end{cases}, if\ 40 \le min_f \le max_f \le 105\ and\ 0 \le \mu_c \le 100, \tag{6}$$

Temperature score:

$$s_f^T = \begin{cases} 50 - |30 - \mu_c| \\ 0, otherwise \end{cases}, if - 40 \le min_f \le max_f \le 150\ and - 20 \le \mu_c \le 120, \tag{7}$$

Velocity score:

$$s_f^v = \begin{cases} \sigma_c + 0.5 \cdot frac_z + 10^{-6} \\ 0\,, otherwise \end{cases}, if\ 0 \le min_f \le 0\ max_f \le 250, \tag{8}$$

Mileage (monotonic) score:

$$s_f^m = \begin{cases} frac_m \cdot max_f, if\ frac_m > 0.95\ and\ max_f > \mu_c \\ 0\,, otherwise \end{cases} \tag{9}$$

3.3 Smoothing and derivatives

Smoothed signals (Savitzky Golay with window w_{SG}, polyorder p=2) is defined

$$\tilde{V}(t) = SG(V(t); w_{SG}\,, 2)\ \ , \tilde{I}(t) = SG(I(t); w_{SG}\,, 2), \ldots.. \tag{10}$$

Discrete gradients

$$\Delta V(t) = \nabla\tilde{V}(t),\ \ \Delta I(t) = \nabla\tilde{\imath}(t),\ \ \Delta T(t) = \nabla\tilde{T}(t),\ \ \Delta SOC(t) = \nabla\widetilde{SOC}(t) \tag{11}$$

3.4 Internal resistance (IR) proxy

The instantaneous IR proxy is computed during current transients as:

$$\tilde{R}_{intn} = \begin{cases} -\frac{\Delta V(t)}{\Delta I(t)+\varepsilon},\ if\ |\Delta I(t)| > 10^{-6} \\ NaN,\ otherwise \end{cases} \tag{12}$$

3.5 Rolling Features

The rolling window length w is set :

$$w = max(10, \lfloor 0.005N \rfloor). \tag{13}$$

For any signal x(t), rolling aggregates is computed as follows:

$$\mu_{x,w}(t) = r_w - mean(x)(t), \sigma_{x,w}(t) = r_w - std(x)(t) \tag{14}$$

$$\min_{x,t}(t) = r_w - min(x)(t) \quad \max_{x,t}(t) = r_w - max(x)(t) \tag{15}$$

These are computed for $x \in \left\{\tilde{V}, \tilde{I}, \tilde{T}, \widetilde{SOC, R_{intn}}\right\}$
The feature vector at time t is constructed as

$$X(t) = \left[\mu_{V,w}(t), \sigma_{V,w}(t), \min_{V,t}(t), \max_{V,t}(t), \ldots \ldots., \Delta V(t), \Delta I(t), \Delta T(t), \Delta SOC(t) \Delta m(t), \Delta v(t)\right] \tag{16}$$

3.5 Isolation Forest

Fit Isolation Forest to the set $\{X(t)\}_{t=1}^{N}$. Denote the model's decision function output at time t by IF(X(t)), where higher values indicate more *normal* samples. The raw anomaly score is defined by:

$$s_{IF}(t) = -IF(X(t)) \tag{17}$$

Normalize to z score :

$$g(t) = zs_{IF}(t) = \frac{s_{IF}(t) - \mu_{s_{IF}}}{\sigma_{s_{IF}} + \varepsilon} \tag{18}$$

Here g(t) is the global anomaly score

3.6 Heuristic (fault-specific) building blocks

The z-normalized building blocks is calculated, where all z-scores are computed over the entire time series unless stated otherwise.

- Current magnitude deviation:$z_I(t) = |z(I(t))|$
- Sudden voltage drop: $z_{dV}(t) = -(\Delta V(t))$
- Temperature rise: $z_{dT}(t) = z(\Delta T(t))$
- IR elevation: $z_{IR}(t) = z\left(\widetilde{R_{intn}}(t)\right)$
- SOC drop while stationary:$z_{SOC,stat}(t) = z\left(-\Delta SOC(t)\right) \cdot 1\{v(t) < 0\}$
- Fast SOC depletion per distance: $z_{\frac{soc}{mile}}(t) = z\left(\frac{-\Delta SOC(t)}{|\Delta m(t)| + \varepsilon}\right)$

3.7 Fault heuristic scores

Each fault-specific heuristic score is constructed as a non-negative combination of the relevant z-normalized building blocks.

- Internal Short Circuit (ISC):
  $$h_{ISC}(t) = [z_I(t)]_+ + [z_{dV}(t)]_+ + [z_{dT}(t)]_+ \tag{19}$$
- Excessive Ageing
  $$h_A(t) = [z_{IR}(t)]_+ + \left[z_{SOC/mile}(t)\right]_+ \tag{20}$$
- Thermal Runaway

$$h_{Thermal\_runaway}(t) = [z_{dT}(t)]_+ + \left[z(-\mu_{V,w}(t))\right]_+ \quad (21)$$

where $\mu_{V,w}(t)$ is the rolling mean of voltage.

- Electrolyte Leakage / Self-discharge

$$h_{Leakage}(t) = \left[z_{SOC,stat}(t)\right]_+ + \left[z(-\mu_{SOC,w}(t))\right]_+ \quad (22)$$

Fusion: combined fault scores

For each fault class $k \in \{ISC, Excessive\ aging, Thermal, leakage\}$ the fused score is defines as,

$$s_k(t) = g(t) + z(h_k(t) \quad (23)$$

This linearly combines the global anomaly evidence g(t) (from Isolation Forest) with the z-scored domain heuristic $h_k(t)$.

The above formulations establish the integration of anomaly detection and heuristic scoring into a unified framework. One aspect of Z normalization is that it makes sure sensor features obtained from different signals are in the same range, whereas the development of heuristic scores from non, negative linear combinations of the appropriate building blocks offers both interpretability and alignment with the domain. The combination of global anomaly scores with fault, specific heuristic scores allows the framework to kill two birds with one stone: figure out when the system is operating abnormally and also get an idea of what kind of a fault causes that behaviour, thus providing both sensitivity and diagnostic insight.

4 Results and discussion

The dataset for this research comes from the article "Model, constrained deep learning for online fault diagnosis in Li, ion batteries over stochastic conditions" published in Nature Communications (2025) [14]. It features more than 18 million data points gathered from 515 electric vehicles of three anonymized manufacturers DTI, QAS, and GIS under both normal and faulty conditions, where faults include electrolyte leakage, internal short circuit, and thermal runaway. The dataset of the GIS model is specifically used for fault diagnosis. Every record consists of voltage, current, temperature, on board SOC, vehicle speed, and odometer readings taken every 30 seconds.This dataset is unbalanced, and the feature distributions of normal and faulty states are overlapping, thus challenging the traditional threshold, based detection. The data variation among different manufacturers improves the model's ability to generalize under stochastic real, world conditions.

The constraint satisfaction based method has an additional feature of determining the safe operating limits for the main battery parameters in the dataset automatically. Table 1 presents a summary of the operational ranges determined for the main battery parameters. Voltages limits are consistent with typical levels of lithium, ion operating, while current values show a discharge, only profile. The temperature range is the normal thermal window coming from the dataset, and the mileage figures represent the beginning of the recorded measurements. These data, driven constraints were combined with the fault detection system so that it could identify any readings that were outside the normal limits. This constraint, based approach to anomaly detection was further supported by adjusting the scores in relation to how close the measurements were to their limits, thus showing its practical value for real, world battery health monitoring.

Table 1. Extracted CSP Constraints from dataset

Parameter	Minimum Value	Maximum Value	Units
Voltage	3.63	4.20	V
Current	-11.74	-9.73	A
Temperature	27.36	34.47	°C
Mileage	9130	11168	miles

Table 2 describes the fault events and anomaly scores. The detection results highlight the model's ability to capture diverse fault modes. Early internal short were detected with high anomaly scores, while severe thermal runaway exhibited the highest peak score of 13.45. Electrolyte leakage appeared in multiple short intervals during mid-cycle operation, whereas excessive ageing faults became dominant in later stages, producing consistently high scores. The peak scores represent the maximum anomaly intensity detected within a fault event. It is computed from the combined anomaly score, which is formed by merging:

- Isolation Forest anomaly output (continuous values)
- Fault-specific heuristic scores (continuous values)
- Z-score normalization (converts all features into fractional, comparable scales)

Because these components produce continuous-valued outputs, the peak score is expressed as a real-number.

Table 2. Detected fault events and anomaly scores using the proposed method .

S. No.	Fault Type	Start Index	End Index	Peak Score
1	Internal Short Circuit	0	11	11.38
2	Electrolyte Leakage	528	583	5.42
3	Electrolyte Leakage	591	594	4.21
4	Internal Short Circuit	850	864	5.73
5	Thermal Runaway	865	877	5.87
6	Internal Short Circuit	1889	1889	4.68
7	Thermal Runaway	2798	2824	7.16
8	Internal Short Circuit	3532	3543	4.52
9	Electrolyte Leakage	3546	3546	4.14
10	Excessive Ageing	3609	3621	7.41
11	Excessive Ageing	3623	3648	11.21
12	Excessive Ageing	3661	3685	9.58
13	Excessive Ageing	3757	3757	4.24
14	Excessive Ageing	3759	3777	11.71
15	Thermal Runaway	3925	3958	13.45

The battery performance metrics of the proposed diagnosis framework are shown in table 2. The unsupervised fault detection framework of the battery, which is part of the proposal, was able to detect 15 battery fault events in the analysed dataset.

On average, the duration of the events was 17.3 14.8 indices, this means that some faults were short in duration, while others lasted for a considerable time. The peak anomaly score per event was 7.38 3.23, illustrating that the fault events deviated largely from the normal operation during the fault occurrence. At the sample level, the Isolation Forest (IF) model marked about 5% of the data points as anomalous, which shows the model's capacity to detect unusual patterns in voltage, current, SOC, temperature, and features derived from them. The average IF score was, 0.0697 0.0615, whereas the threshold at the 95th percentile was established at 4.12, thus, offering a numerical model for discriminating anomalies from normal operation. In general, the findings indicate that the isolation forest along with the fault, specific heuristics can effectively detect the sudden and major battery abnormalities such as internal short circuits and thermal events while the slow ageing of the battery needs complementary analysis. The metrics derived from the methods give quantitative proof of the sensitivity, specificity, and the capability in the detection of the system thereby it is suitable for not only real, time battery health monitoring but also for predictive maintenance.

Table 3. Performance metrics of the proposed method

.

Metric	Description	Value
Events detected	Total fault events flagged	15
Mean event duration	indices	17.3 Â± 14.8
Peak anomaly score	Max per event	7.38 Â± 3.23
Fraction of samples flagged	Anomaly samples / total	0.05
IF score mean Â± std	Isolation Forest raw score	-0.069738 Â± 0.061452
Top score threshold	95th percentile threshold	4.124923
IR proxy mean Â± std	Internal resistance proxy	-0.3224 Â± 42.0076
SOC drop rate mean Â± std	SOC drop per index	-0.0087 Â± 0.0864
Temperature rise mean Â± std	dT per index	-0.0008 Â± 0.0315
Internal Short Circuit correlation	Heuristic vs IF score	0.642
Excessive Ageing correlation	Heuristic vs IF score	0.073
Thermal Runaway correlation	Heuristic vs IF score	0.395

The battery fault events timeline of figure 2 shows the time location of different fault types during the whole operation period. The excessive ageing faults are the ones that have been protruding more and more at the later time indices, thus the progressive degradation behaviour is very much indicated. Other faults like thermal Runaway, electrolyte leakage, and Internal Short Circuit are randomly spread throughout the timeline which means that the anomalies are not regular.

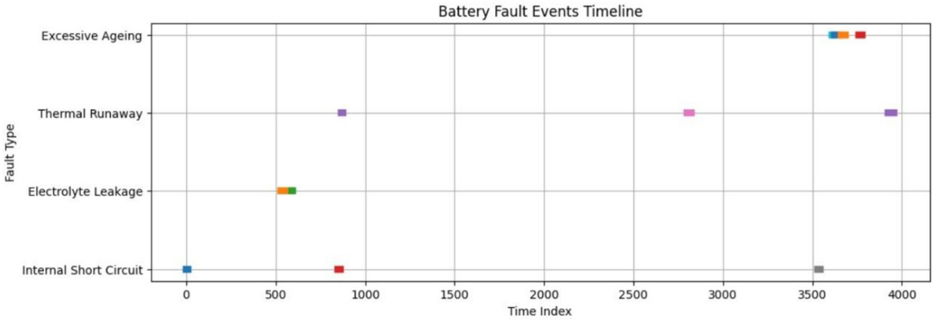

Fig. 2. Battery Fault timeline

The frequency of detected faults plot shown in figure 3 reinforces the fact that ageing excessively has been the main fault with Internal Short Circuit being the second most common fault. Electrolyte leakage and thermal Runaway occur much less frequently.
This means that ageing, related degradation has been the main cause of system faults in the evaluated dataset

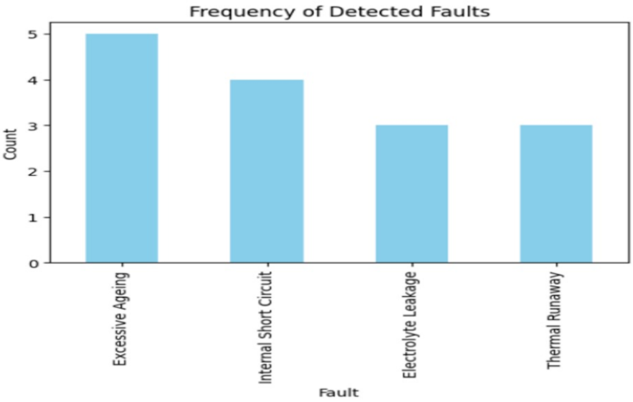

Fig. 3. Frequency of detected faults.

5 Conclusion

The framework that has been proposed is a step in the right direction when it comes to diagnosing faults in lithium, ion batteries, as it essentially merges isolation forest with fault, specific rules to achieve this goal. It attained a high level of success in detecting a diverse range of faults most notably, internal short circuits, thermal problems, and electrolyte leakages with their durations and severities respectively. There was less than a fraction of the data that was declared as abnormal, and this reflects that the model is sensitive and selective rather than being overly reactive.

Moreover, the use of additional signal, based features such as the measuring of the internal resistance, SOC drop rate, and the rate at which the temperature changes allowed for a more precise characterization of each fault. The correlation analysis revealed that abrupt faults, for instance, internal short circuit, were among the most accurately identified, while the gradual patterns of degradation were present to a lesser extent. Overall, the approach enables timely and reliable fault detection, increases the safety of the operation, and is compatible with real, time battery health monitoring in a variety of settings.

References

1. J. Zhang, Y. Wang, B. Jiang, H. He, S. Huang, C. Wang, Y. Zhang, X. Han, D. Guo, G. He, M. Ouyang, Realistic fault detection of Li-ion battery via dynamical deep learning. Nat. Commun. 14, 5940 (2023). https://doi.org/10.1038/s41467-023-41689
2. A. Naha, A. Khandelwal, S. Agarwal, P. Tagade, K.S. Hariharan, A. Kaushik, A. Yadu, S.M. Kolake, S. Han, B. Oh, Internal short circuit detection in Li-ion batteries using supervised machine learning. Sci. Rep. 10, 1301 (2020). https://doi.org/10.1038/s41598-020-58298-0
3. J. Ouyang, Z. Lin, L. Hu, X. Fang, Voltage faults diagnosis for lithium-ion batteries in electric vehicles using optimized graphical neural network. Sci. Rep. 15, 27328 (2025). https://doi.org/10.1038/s41598-025-01234-5
4. Q. Xue, G. Li, Y. Zhang, S. Shen, Z. Chen, Y. Liu, Fault diagnosis and abnormality detection of lithium-ion battery packs based on statistical distribution. J. Power Sources 482, 228964 (2021). https://doi.org/10.1016/j.jpowsour.2020.228964
5. G. Hu, P. Huang, Z. Bai, Q. Wang, K. Qi, Comprehensive analysis of failure evolution and safety evaluation of automotive lithium-ion battery. ETransport. 10, 100140 (2021). https://doi.org/10.1016/j.etran.2021.100140
6. R.K. Daniels, V. Kumar, S.S. Chouhan, A. Prabhakar, Thermal runaway fault prediction in air-cooled lithium-ion battery modules using machine learning through temperature sensors placement optimization. Appl. Energy 355, 122352 (2024). https://doi.org/10.1016/j.apenergy.2023.122352
7. X. Liu, Y. Li, X. Jiang, K. Xu, Lithium-ion battery of an electric vehicle short circuit caused by electrolyte leakage: A case study and online detection. J. Energy Storage 97, 112950 (2024). https://doi.org/10.1016/j.est.2024.112950
8. X. Feng, M. Ouyang, X. Liu, L. Lu, Y. Xia, X. He, Thermal runaway mechanism of lithium-ion battery for electric vehicles: A review. Energy Storage Mater. 10, 246–267 (2018). https://doi.org/10.1016/j.ensm.2017.05.013
9. Z. Liao, S. Zhang, K. Li, G. Zhang, T.G. Habetler, A survey of methods for monitoring and detecting thermal runaway of lithium-ion batteries. J. Power Sources 436, 226879 (2019). https://doi.org/10.1016/j.jpowsour.2019.226879
10. L. Song, Y. Zheng, Z. Xiao, C. Wang, T. Long, Review on thermal runaway of lithium-ion batteries for electric vehicles. J. Electron. Mater. 51, 30–46 (2022). https://doi.org/10.1007/s11664-021-09263-3
11. Y. Zhang, R. Xiong, H. He, X. Qu, M. Pecht, Aging characteristics-based health diagnosis and remaining useful life prognostics for lithium-ion batteries. ETransport. 1, 100004 (2019). https://doi.org/10.1016/j.etran.2019.100004
12. S. Park, Y. Song, S.W. Kim, Simultaneous diagnosis of cell aging and internal short circuit faults in lithium-ion batteries using average leakage interval. Energy 290, 130220 (2024). https://doi.org/10.1016/j.energy.2024.130220
13. Y. Liao, H. Zhang, Y. Peng, Y. Hu, J. Liang, Z. Gong, Y. Wei, Y. Yang, Electrolyte degradation during aging process of lithium-ion batteries: mechanisms,

characterization, and quantitative analysis. Adv. Energy Mater. 14, 2304295 (2024). https://doi.org/10.1002/aenm.202304295

14. R. Cao, Z. Zhang, R. Shi, J. Lu, Y. Zheng, Y. Sun, X. Liu, S. Yang, Model-constrained deep learning for online fault diagnosis in Li-ion batteries over stochastic conditions. Nat. Commun. 16, 1651 (2025). https://doi.org/10.1038/s41467-025-01915-7