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Advanced fault diagnosis in batteries: Insights into fault mechanisms, sensor fusion, and artificial intelligence

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ABSTRACT

With the increasing demand for sustainable and clean energy, lithium-ion batteries have emerged as one of the most essential energy storage technologies. However, safety concerns have become a major bottleneck, significantly constraining their widespread deployment. This highlights the critical need for efficient fault diagnosis to ensure the safe and reliable operation of battery systems. In recent years, artificial intelligence (AI) techniques, in combination with advanced sensing technologies, have attracted growing attention for battery fault diagnosis and prognosis. Nevertheless, their full potential and broad applicability remain underexplored. This review provides a systematic analysis of the integration of AI methodologies with advanced sensors, emphasizing their capabilities for accurate fault detection and prediction, while also identifying key challenges and future research directions in this evolving field. The study begins by outlining common battery fault types and their underlying mechanisms, offering a foundational understanding of the associated complexities. It then introduces state-of-the-art AI techniques applied in fault diagnosis. Then, recent advances in combining AI with advanced sensing technologies for battery diagnostics are examined. Finally, the limitations of current approaches are discussed, and promising directions are proposed to facilitate the development of intelligent, scalable, and robust fault diagnosis frameworks for lithium-ion battery systems.

1. Introduction

The transportation and energy storage sectors have been at the forefront of global electrification efforts, driven by the increasing adoption of sustainable energy solutions [1,2]. Lithium-ion batteries (LIBs), owing to their high energy density and low self-discharge rate [3,4], are widely regarded as an efficient energy storage medium and have been extensively deployed in applications such as electric vehicles (EVs) and smart grids [5,6]. However, with the frequent occurrence of fire accidents in EVs and energy storage systems (ESSs) caused by failures of LIBs under extreme operating conditions and harsh environments [7,8], their safety has received more widespread attention in recent years [9,10]. Therefore, the fault diagnosis of LIBs has become a critical research area with substantial practical implications [11].

As high-density energy storage devices [12], LIBs possess a certain degree of instability [13,14]. Material distribution defects and structural design flaws introduced during manufacturing, along with electrical or mechanical abuse during operation, can lead to various battery failures, such as internal short circuit (ISC), external short circuit (ESC), overcharge, and over-discharge [15,16], all of which may compromise the normal operation of the battery system [17,18]. Moreover, failures are not limited to the battery cells themselves. Peripheral components such as sensors, connectors, and control circuits may also experience faults during operation, further degrading system reliability and efficiency. Importantly, these failures are neither isolated nor static, they often interact and may be exacerbated under extreme environmental conditions [19]. For example, overcharging batteries at low temperatures can lead to the growth of lithium dendrites [20], which in turn increases the risk of ISC and thermal runaway, potentially resulting in severe

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List of abbreviations

AI	artificial intelligence
LIBs	lithium-ion batteries
EVs	electric vehicles
ESSs	energy storage systems
ISC	internal short circuit
ESC	external short circuit
SOC	state of charge
BMS	battery management system
SVM	support vector machine
RF	random forest
ANN	artificial neural network
KSVM	kernel space support vector machine
RVM	relevance vector machine
ECM	equivalent circuit model
LSTM	long short-term memory
RNN	recurrent neural network
CNN	convolutional neural network
GRNN	gated recurrent neural network
DBSCAN	density-based spatial clustering with noise
LOF	local outlier factor
AE	autoencoder
GAN	generative adversarial network
VAE	variational autoencoder
GRU	gated recurrent unit
EIS	electrochemical impedance spectroscopy
DNN	deep neural network
DRT	distribution relaxation time
FBG	fiber Bragg grating
SOH	state of health
BP	back propagation
VGG	visual geometry group
PINN	physical information neural network

consequences [21]. Therefore, timely and accurate diagnosis of battery faults is essential to prevent their further development and deterioration.

The critical importance of fault detection and diagnosis for safe and reliable battery operation has motivated extensive research in this field, with several review articles summarizing the progress achieved and the challenges that remain. Zhang et al. [22] provided an overview of experimental methods and detection techniques for battery ISC, while Janakiraman et al. [23] focused specifically on the detection methods of lithium plating. In [24,25], the methods used for battery system fault diagnosis were classified and discussed. Specifically, fault diagnosis methods can be primarily categorized into two groups: model-based and non-model-based methods. The performance of model-based methods is largely dependent on the accuracy and fidelity of the battery model. However, constructing high-precision models remains a significant challenge due to the inherently complex and highly nonlinear internal behavior of batteries. Non-model-based methods primarily include signal processing techniques and artificial intelligence (AI)-based approaches. Signal processing-based methods are often sensitive to noise interference, which can result in misdiagnosis. In contrast, AI-based methods have developed rapidly in recent years, offering advantages such as high diagnostic accuracy, strong ability to capture nonlinear dynamics, and reduced dependence on domain-specific expert knowledge [26].

However, most AI-based battery fault diagnosis algorithms have been developed using battery voltage, current, and surface temperature data [27]. While these measurements are readily accessible, they provide limited insight into the battery's internal state and often respond slowly. This significantly constrains the application of AI in understanding fault mechanisms and developing higher-performance diagnostic solutions. As a result, integrating AI algorithms with advanced sensing instruments to explore fault mechanisms and enhance diagnostic capabilities has emerged as a key development trend [28]. Despite recent progress, existing reviews on battery fault diagnosis have not addressed the topic in a systematic and in-depth manner, with most focusing on AI and advanced sensing technologies separately. In this context, this study aims to fill this gap by providing a detailed examination of the development and integration of AI and sensor technologies. The specific contributions of the work are summarized as follows.

1. An overview of common battery failures and their underlying mechanisms is presented, including basic definitions, triggering factors, and developmental processes. Based on this foundation, a systematic introduction to AI-based fault diagnosis methods is provided. Notably, besides the conventional supervised and unsupervised categories, semi-supervised learning is introduced as a new category of fault diagnosis approaches.
2. For the first time, the integration of AI algorithms with advanced sensors, such as electrochemical impedance spectroscopy (EIS), optical fiber sensors, and ultrasonic sensors, is systematically summarized in the context of battery fault diagnosis. Detailed discussions of the advantages and limitations of these integrated approaches are also provided.
3. The key challenges in adopting and implementing AI combined with advanced sensors for enhanced battery fault diagnosis are outlined, and potential opportunities and future research directions are highlighted to further advance the field.

The remainder of this study is structured as follows: Section 2 analyses various faults of battery system at different stages, focusing on their causes, evolution trends, and characteristic states. Section 3 classifies the application of AI technologies in the diagnosis of battery faults, followed by a detailed discussion of combining AI and advanced sensors to improve battery fault diagnosis in Section 4. Section 5 presents the current limitations and future research directions related to the combined application of AI and advanced sensing technologies for battery fault diagnosis. Finally, Section 6 summarizes the whole study.

2. Overview of battery faults and their mechanisms

The types of faults that would occur in the battery system mainly include ISC, ESC, overcharge, over-discharge, lithium plating, electrolyte leakage fault, connection fault, sensor fault, and thermal runaway. Table 1 summarizes the qualitative description of each fault type in battery systems. This section provides a systematic overview of the above-mentioned battery failures and their underlying mechanisms. It describes typical manifestations, triggering factors, failure evolution, impacts on system safety and performance, as well as the coupling and causal relationships among different failure modes.

2.1. ISC fault

ISC failure occurs when the battery separator is damaged or ruptured, resulting in direct contact between the positive and negative electrodes [29]. It is typically accompanied by abnormal voltage drops, local temperature rises, current fluctuations, SOC estimation deviations, and accelerated capacity degradation. In the early stages, these anomalies are often subtle and difficult to detect. As the fault progresses, however, it can trigger a rapid exothermic chain reaction, leading to a sharp temperature rise and, ultimately, thermal runaway with

Table 1
Description of each fault may occur in battery system.

Fault type	Description	Ref
ISC fault	The discharge caused by potential difference and accompanied by heat generation when the positive and negative electrode materials inside the battery are connected each other.	[21, 29]
ESC fault	The abnormal discharge caused by the direct connection of positive and negative electrode of battery.	[30]
Overcharge fault	The behavior of charging the battery beyond its charging cut-off voltage.	[33]
Over-discharge fault	The behavior of discharging the battery below its discharging cut-off voltage.	[32, 38]
Lithium plating	The phenomenon where lithium-ions fail to intercalate into the anode and instead deposit as metallic lithium on its surface.	[43, 44]
Electrolyte leakage fault	The phenomenon of electrolyte leaking inside the battery due to damage to the packaging, structure or external factors.	[47]
Connection fault	Abnormal connection between adjacent cells in the battery system.	[51, 52]
Sensor fault	Sensors in the battery system fail to work properly, resulting in loss, inaccuracy, or failure of measurement data.	[53, 54]
Thermal runaway	The phenomenon occurs when the battery temperature exceeds a critical threshold, triggering a chain reaction that leads to uncontrollable heating and eventually combustion or explosion.	[57]

potentially catastrophic consequences. Statistics show that more than half of battery fire incidents are associated with ISC faults [30].

ISC faults usually have two triggering factors: internal defects and battery abuse [22]. Internal defects primarily involve separator and electrode issues, such as cracks in the separator, burrs on the electrodes, and contamination introduced during manufacturing. Battery abuse can be classified into electrical and mechanical categories [31]. Electrical abuse, including overcharging and over-discharging during operation, accelerates lithium dendrite growth. These dendrites can pierce the separator, resulting in ISC faults, as illustrated schematically in Fig. 1. Mechanical abuse, such as collisions or drops, can crush or puncture the cell, directly inducing ISC. Additionally, the severity of an ISC fault is typically evaluated based on the self-discharge rate and heat generation rate, and it is classified into three stages: initial, middle and terminal [32]. Fig. 2 presents the corresponding thermal and electrical characteristics at each stage. In the initial stage, the equivalent resistance remains relatively high, leading to slow voltage decay and negligible heat generation. The resulting anomalies are subtle, with limited influence on system performance, and thus are often overlooked, causing missed opportunities for timely intervention. As the fault progresses to the middle stage, the ISC resistance decreases, resulting in higher short-circuit current, accelerated voltage drop, and increased heat generation. This can cause significant local temperature rise and capacity degradation, thereby compromising battery performance and elevating safety hazards. In the terminal stage, rapid temperature escalation causes separator failure and enlarges the short-circuit contact area. The terminal voltage collapses to zero, triggering exothermic side reactions that lead to thermal runaway, accompanied by smoke, fire, or even explosion. The concealed nature of ISC faults in the early stage, coupled with their rapid escalation and severe consequences in the later stage, makes them a leading cause of battery safety incidents and a critical threat to both system reliability and personnel safety.

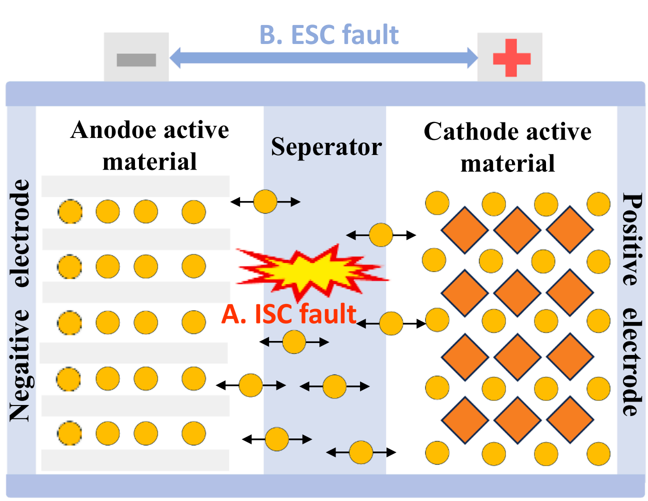

Fig. 1. Schematic diagram of ISC and ESC faults.

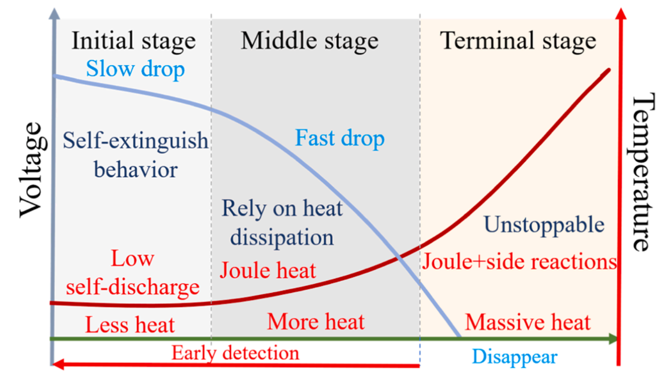

Fig. 2. Thermal and electrical characteristics of ISC failure at various stages.

2.2. ESC fault

ESC failure refers to the direct connection between the positive and negative terminals through the external circuit of the battery. It is typically characterized by a sudden voltage drop, an instantaneous surge in current, and a rapid rise in the battery's surface temperature [33]. Compared with ISC faults, the triggering mechanism of ESC faults is relatively straightforward. Factors such as collision deformation of the battery system shell, water immersion, and failure of the connecting wires can all lead to an ESC fault. Once an ESC fault occurs, it progresses rapidly. Owing to the low internal resistance of the battery, a large short-circuit current is generated, causing a sharp voltage drop and substantial irreversible heat, which further leads to a rapid temperature rise. Although the peak temperature reached during an ESC fault is comparable to that of an ISC fault, the heating rate is significantly faster and the time to reach peak temperature is much shorter. As the temperature continues to increase and exceeds the thermal stability limit of the separator, the separator shrinks and decomposes, which may induce uncontrollable ISC or even thermal runaway.

The severity of an ESC fault is highly correlated with the initial SOC and its duration. Batteries with higher SOC generally produce larger discharge currents and greater temperature rises, whereas lower SOC results in smaller discharge currents and less structural damage. However, regardless of the SOC, once an ESC fault occurs, if the protection mechanism fails or the response is delayed, it may lead to electrolyte decomposition, gas release, and even severe safety incidents such as thermal runaway, fire, or explosion. Therefore, rapid identification and timely disconnection of the circuit are essential to ensure system safety.

2.3. Overcharge/ over-discharge fault

Overcharge failure occurs when a battery is charged beyond its designated cut-off voltage. It is a common yet highly hazardous fault, typically characterized by a continuous rise in voltage, abnormal temperature elevation, cell swelling, and gas evolution [34]. In practical applications, overcharge faults are usually caused by charger malfunctions or sensor failures, while battery inconsistencies, high charging rates, and fast charging near the end of the cycle further increase the risk [35]. According to severity, overcharge faults can be categorized into mild and severe types, both of which significantly affect battery performance [36,37]. Mild overcharge may exert limited short-term effects, but over time it accelerates polarization, leading to capacity degradation, reduced system performance, and increased safety risks [38]. Severe overcharge, by contrast, can result in catastrophic consequences such as complete battery failure and thermal runaway, accompanied by fire or explosion [39]. Specifically, severe overcharge can cause positive electrode melting, transition metal dissolution, phase transformations in electrode materials, and extensive lithium plating on the negative electrode surface. These effects reduce the thermal stability of the negative electrode and accelerate the battery's temperature rise. In particular, lithium plating promotes dendrite formation, which may pierce the separator, induce ISC, and ultimately trigger thermal runaway, posing a severe threat to system safety.

Contrary to overcharge faults, over-discharge faults occur when the battery is discharged below its cut-off voltage. Although generally considered less harmful than overcharge faults, they still pose significant risks. Common causes include sensor malfunctions, ESC failures, and cell inconsistencies [40]. Deep over-discharge can lead to irreversible changes, such as significant capacity loss, increased impedance, and solid electrolyte decomposition between phases, potentially triggering thermal runaway [41,42]. While deep over-discharge is more easily detected by monitoring discharge voltage, slight over-discharge remains difficult to identify in a timely manner due to cell inconsistencies [43]. Prolonged slight over-discharge can gradually degrade performance, causing irreversible capacity loss and reducing the overall efficiency of the ESS. Therefore, it is crucial to detect over-discharge faults, including those that may have occurred in the past.

2.4. Lithium plating

Lithium deposition refers to the reduction of lithium-ions on the negative electrode (typically graphite) during the charge–discharge process of a LIB, resulting in the formation of metallic lithium on the electrode surface. This phenomenon can lead to increased internal resistance, abnormal voltage fluctuations, accelerated capacity degradation, and localized temperature rise [44]. It typically occurs under abnormal charging conditions, particularly during overcharging, low-temperature operation, high charging rates, or as the battery ages [45].

Lithium plating is generally classified into reversible and irreversible types. Irreversible lithium plating not only reacts with the electrolyte but also becomes electrically isolated from the negative electrode, both of which contribute to the irreversible loss of active lithium and capacity. In severe cases, the accumulated lithium may form dendrites that grow and penetrate the separator, potentially triggering ISC failure and posing significant safety risks to the system [46]. The reversible part refers to the lithium that remains in electrical contact with the negative electrode interface, allowing it to undergo a charge transfer reaction into the electrolyte and then re-embed into the negative electrode. Although reversible lithium plating does not cause lithium loss, it lowers the onset temperature for thermal runaway, leading to potential safety concerns [47].

2.5. Electrolyte leakage fault

Electrolyte leakage is a typical failure of LIBs that significantly compromises reliability. It is usually characterized by visible liquid seepage or an unusual odor from the battery casing. This issue is often caused by factors such as inadequate packaging, external mechanical damage, overcharging, over-discharging, or exposure to excessive temperatures [48]. Once leakage occurs, battery performance deteriorates significantly, manifested by reduced rated voltage and capacity as well as increased internal resistance [49]. Additionally, certain components in the electrolyte are toxic, and leakage can result in environmental pollution [50]. In extreme cases, leaked electrolyte may react with ambient moisture to generate hydrofluoric acid, which corrodes internal components such as active materials, solid electrolyte interphase films, and current collectors. Furthermore, electrolyte vapor raises the conductivity of the surrounding air. If a large current flows through an air gap in the circuit, an arc may form under certain conditions, generating an instantaneous high temperature that can ignite the battery. This process may further lead to the explosion of the entire pack, posing a severe threat to the performance and safety of the ESS [51]. Therefore, timely intervention is essential to mitigate the significant risks associated with electrolyte leakage failure.

2.6. Connection fault

Battery connection faults are issues in the electrical connection between battery cells, which prevent the battery system from functioning properly or cause its performance to degrade. Specifically, bolts or welds used for intercell connections are particularly vulnerable to external forces and may loosen or deteriorate over time [52]. When such faults occur, the resulting increase in connection resistance leads to excessive heat generation, posing a threat to thermal safety. Moreover, connection faults can cause current imbalances across the parallel branches of the battery system, accelerating the degradation of the system's power performance. The voltage variations resulting from increased internal resistance during battery aging closely resemble those observed in connection faults. As a result, relying solely on voltage data makes it challenging to accurately distinguish between battery aging and connection faults during fault diagnosis [53].

2.7. Sensor fault

Sensor faults refer to failures in sensors used to monitor battery parameters, resulting in data loss, inaccuracies, or complete measurement failure. Such faults impair the BMS's ability to accurately evaluate and regulate battery status [54]. In practical applications, sensor faults are usually caused by inherent defects, aging and harsh operating conditions. Common battery sensors include temperature sensors, current sensors, and voltage sensors, all of which are critical for monitoring battery health, managing charge and discharge cycles, and ensuring safety protection [55]. A malfunctioning voltage sensor can compromise overcharge and over-discharge protection strategies that rely on cut-off voltage thresholds, thereby increasing the risk of overcharging or over-discharging. Current sensor faults may lead the BMS to misinterpret the battery's operating state, issuing incorrect control commands. For instance, this could result in errors in battery SOC calculations, leading to improper balancing strategies that increase battery system inconsistency [56]. Temperature sensor faults may cause the battery thermal management system to issue incorrect control commands, leading to an increased temperature difference among cells or causing the battery temperature to deviate from its normal operating range, thereby elevating the risk of thermal runaway [57].

2.8. Thermal runaway

Thermal runaway occurs when the internal temperature of a battery exceeds a critical threshold during operation, initiating a chain reaction that leads to an exponential increase in temperature and accelerates thermal degradation. Typical manifestations include a rapid rise in battery temperature, swelling of the battery casing, smoke emission, fire, and potentially explosion [58]. In practical applications, there are numerous triggering factors for thermal runaway, as shown in Fig. 3. In addition to electrical and mechanical abuse, thermal runaway can also be caused by thermal abuse resulting from extreme environmental

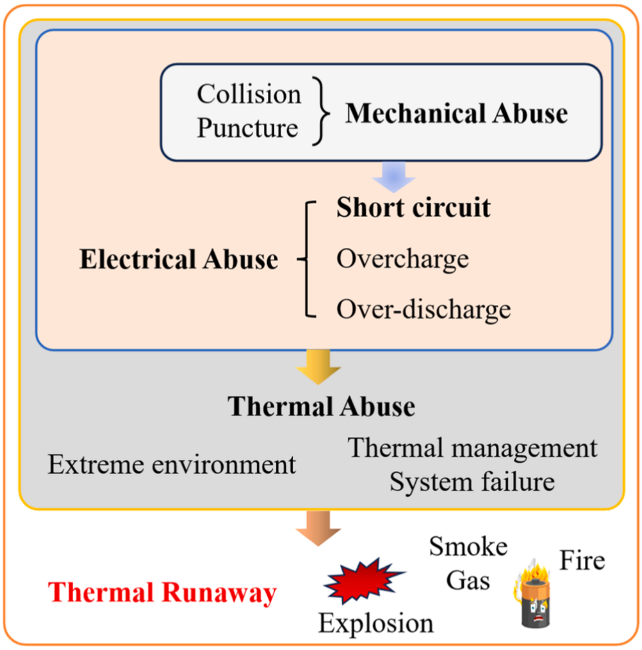

Fig. 3. Thermal runaway trigger factors.

conditions and failures in the thermal management system [59].

The progression of thermal runaway chain reactions can be systematically categorized into three distinct stages [60]. First, the thermal runaway chain reaction begins with the decomposition of the solid electrolyte interface (SEI), leading to an abnormal increase in temperature. This triggers a side reaction between the electrolyte and the anode, gradually accumulating heat and causing the electrolyte to evaporate [61]. As the temperature continues to rise and reaches the critical point for the main heat release, the diaphragm begins to shrink and decompose. This causes a widespread ISC and intensifies the redox reactions, accelerating the temperature rise [62]. At this stage, the reaction generates large amounts of gases such as carbon dioxide, carbon monoxide, and hydrogen. The accumulation of these gases leads to a rapid increase in internal pressure, causing the battery casing to expand. Finally, when the internal pressure exceeds the threshold set by the exhaust valve, the high-pressure gas is ejected from the battery at high speed, often accompanied by audible sounds and visible smoke [63]. Moreover, when a large volume of high-temperature combustible gas mixes with surrounding air, it can ignite, causing an open flame or even an explosion. Once thermal runaway is triggered, it rapidly propagates throughout the battery pack, resulting in more severe consequences, significant safety hazards to the system, and potentially causing damage to the entire ESS [64].

2.9. Coupling relationships of various types of faults

The preceding sections have outlined the major types of battery faults, offering fundamental insights into the challenges and complexities associated with fault diagnosis. It is important to note that these fault types do not occur in isolation; instead, they are often interrelated and exhibit complex causal relationships, as illustrated in Fig. 4. For example, overcharging can trigger lithium plating and dendrite growth, which may puncture the separator and cause an ISC, ultimately leading to thermal runaway. Severe over-discharge can dissolve copper from the anode current collector, which may redeposit and pierce the separator, again initiating ISC and thermal runaway. Environmental factors further

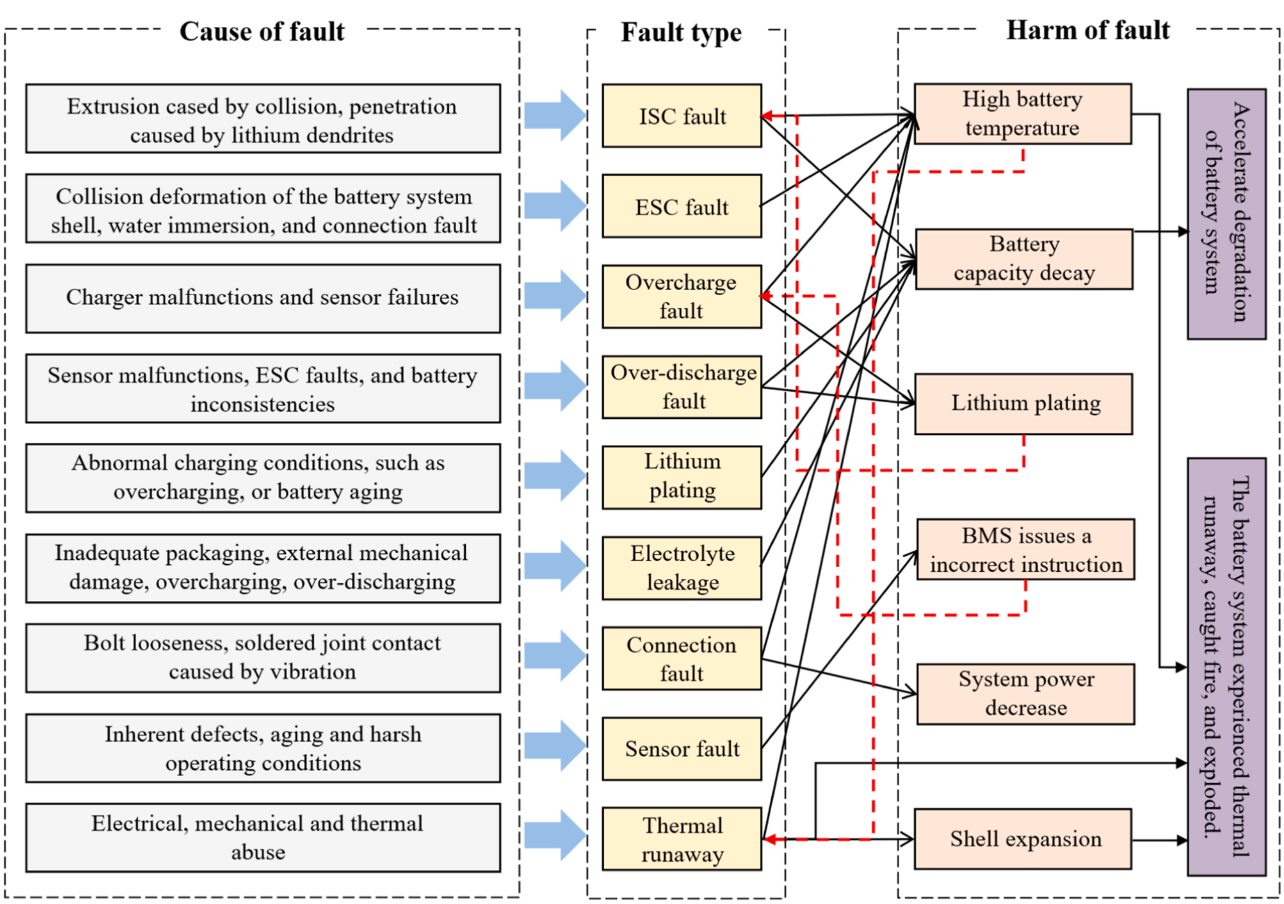

Fig. 4. Causes and coupling relationships of battery system faults.

accelerate fault propagation: low temperatures promote dendrite formation, while high temperatures intensify side reactions, both potentially leading to catastrophic outcomes. In addition, failures of peripheral components—such as sensor errors or loose connectors—can distort system perception and induce secondary faults, highlighting that a primary abnormality can escalate into a chain of failures. Although certain faults present obvious voltage and temperature signatures, the overlap of such signals across different fault modes complicates reliable identification, underscoring the limitations of conventional diagnostic methods.

These challenges call for more advanced approaches capable of handling nonlinearities, hidden correlations, and high-dimensional fault features that traditional threshold-based methods cannot resolve. In this context, artificial intelligence offers powerful tools for learning complex patterns from operational data, enabling improved fault detection, classification, and prediction. Section 3 therefore provides a systematic review of AI-based battery fault diagnosis methods.

3. AI-based battery fault diagnosis

Extensive research has been conducted on AI-based fault diagnosis for various battery system failures [65]. As illustrated in Fig. 5, the general process of AI-based fault diagnosis typically involves several steps. First, sensors and data acquisition systems record cell voltage, current, and temperature, and the raw data is pre-processed to ensure quality and integrity. Next, feature extraction and selection are carried out to identify the feature subset used for model training. The dataset is then randomly divided into training and test sets. The training set is used to fit the model and tune hyperparameters to achieve optimal performance, while the test set is employed to evaluate the model's generalization ability. Based on the evaluation results, further adjustments to the model or feature selection may be made to enhance performance. Finally, the trained model is applied for anomaly detection or fault classification to complete the diagnostic process. In this process, AI plays a crucial role in signal processing, multi-source data fusion, anomaly feature extraction, fault identification, and trend prediction. By leveraging machine learning techniques such as tree-based models and neural networks, AI can extract latent fault patterns from complex signals. This capability improves diagnostic accuracy and real-time responsiveness, thereby significantly advancing the intelligent management of battery systems.

As shown in Fig. 6, the AI technologies used for battery fault diagnosis can be divided into supervised learning, unsupervised learning, and semi-supervised learning according to their different training ways [66,67]. The following summarizes these three AI approaches for battery fault diagnosis and analyzes their specific functions and limitations.

3.1. Supervised learning

Supervised learning is an AI training approach in which an algorithm learns a predictive model from labelled training data containing both input features and their corresponding output labels. During training, the model captures the mapping relationship between inputs and outputs, enabling it to make predictions on new, unseen data [68]. In the context of fault diagnosis, supervised learning can effectively model diverse battery operating conditions and failure modes, demonstrating strong performance in identifying different fault types. However, its development and practical application are constrained by the limited availability of fault datasets and the difficulty of obtaining accurately labelled samples. The algorithms commonly used in supervised learning for battery fault diagnosis are: support vector machine (SVM), random forest (RF) and artificial neural network (ANN) [68]. The following section presents an overview of fault diagnosis research based on these algorithm types, accompanied by a detailed analysis of their respective advantages and limitations.

3.1.1. Support vector machine

SVM is an AI method based on statistical learning theory, widely applied in classification, regression, and pattern recognition. Its core principle is to construct an optimal hyperplane that separates data points of different categories while maximizing the margin, thereby enhancing generalization ability. Beyond linearly separable cases, SVM employs kernel functions, such as the radial basis function (RBF), to project data into higher-dimensional spaces for effective nonlinear problem solving [69]. In battery fault diagnosis, SVM classifies different health states or fault types by mapping parameters such as voltage, temperature, and capacity into a high-dimensional space and identifying the separating hyperplane between normal and fault states. This classification capability enables accurate fault identification and diagnosis, thereby supporting improved battery management and safety [44]. Yao et al. [70] proposed an SVM-based fault diagnosis method for series battery packs, capable of identifying both fault states and severity. A discrete cosine filter was applied to suppress noise, and grid search was used to optimize kernel parameters and the penalty factor. The method achieved over 94 % detection accuracy with an identification time below 0.1 s. However, its validation was limited to a four-cell module, raising concerns about applicability to large-scale battery systems. Similarly, Zhang et al. [71] proposed a battery fault diagnosis method based on online least squares SVM, enabling the identification of

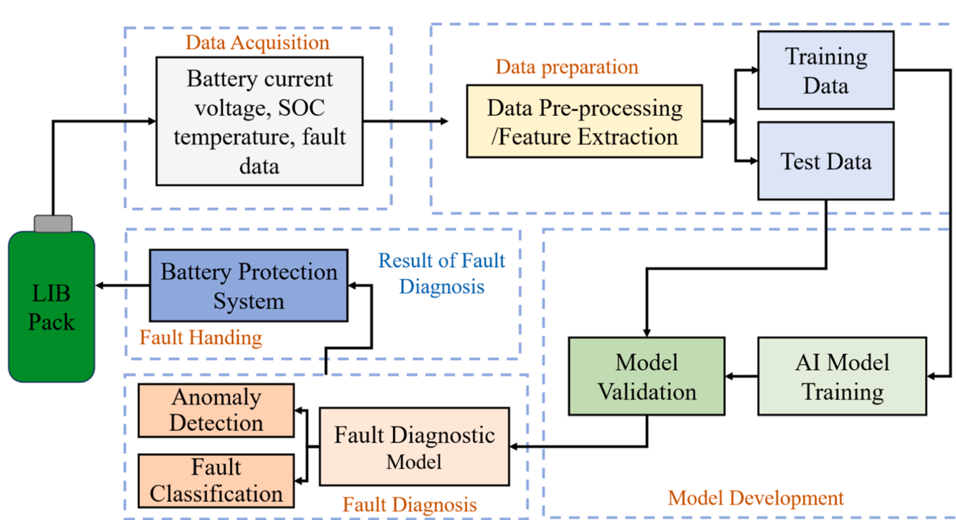

Fig. 5. General process of AI-based fault diagnosis solution.

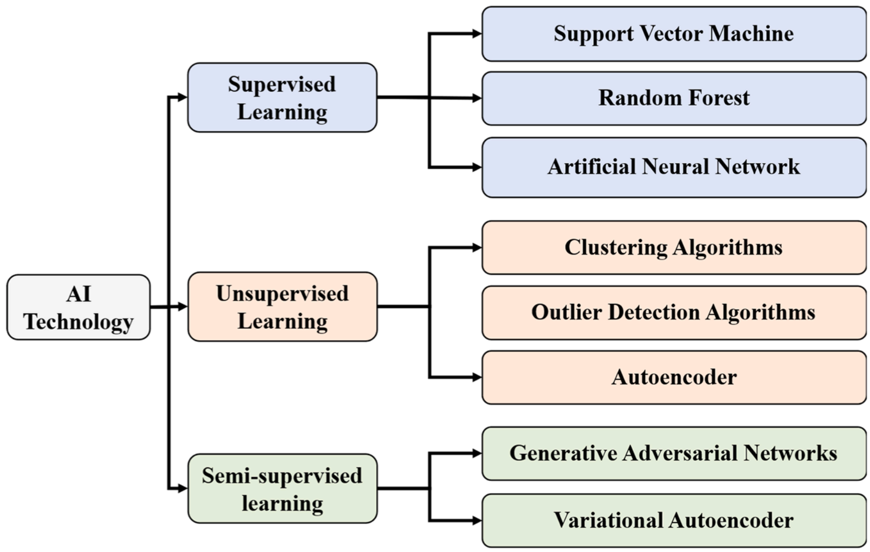

Fig. 6. Classification of AI technologies for LIB fault diagnosis.

overcharge and over-discharge faults. However, due to the limitations of conventional SVM in handling nonlinear data, this method relies on constant current charging and discharging conditions, and the identified faults are primarily rapid faults characterized by distinct abrupt voltage changes. As a result, concerns have been raised regarding its effectiveness under real-world operating conditions, which are often dynamic and involve gradual fault evolution. To address these limitations, two improved variants of SVM—kernel support vector machine (KSVM) and relevance vector machine (RVM)—have also been explored for battery fault diagnosis. Deng et al. [72] employed KSVM to classify faulty and non-faulty battery cells, demonstrating higher efficiency than traditional SVM. The improvement is attributed to the RBF kernel's ability to capture battery characteristics and operating behavior, leading to enhanced classification performance and 98 % accuracy on laboratory data. Xie et al. [73] developed a centralized thermal evolution model based on an equivalent circuit model (ECM) to obtain the thermal and electrical characteristics of ISC failures. They then applied a multi-class RVM to evaluate these characteristics and quantify the degree of ISC. This approach can more accurately and comprehensively assess the severity of ISC faults in battery systems, but is accompanied by a high memory requirement due to the increased training data requirements.

In summary, SVM exhibits strong adaptability to nonlinear systems and has demonstrated robust performance in single-fault detection and anomaly identification in battery fault diagnosis. However, several limitations remain: (1) The selection of an appropriate kernel function is critical to model performance, yet remains a challenging and often empirical task. (2) SVM is more suitable for small-scale battery fault datasets, as an increase in training data substantially raises the number of support vectors, leading to significant computational overhead. (3) Although SVM can handle nonlinear data through kernel functions, its effectiveness diminishes under complex dynamic conditions and in the presence of gradual faults with weak features, typically requiring elaborate feature engineering to maintain diagnostic accuracy.

3.1.2. Random forest

RF is a tree-based algorithm that enhances the accuracy and robustness of battery fault diagnosis by integrating the predictions of multiple decision trees. Each tree is trained on randomly selected subsets of data and features, enabling the model to capture complex relationships in the battery state. Through this ensemble approach, RF can diagnose various failures, such as ISC, overheating, and performance degradation, by classifying operating parameters or extracted features [74]. In addition, its tree-based structure allows for the evaluation of feature importance, improving interpretability and facilitating the identification of key fault indicators. These advantages make RF a practical and effective tool for data-driven battery health monitoring.

Currently, RF-based fault diagnosis research primarily targets gradual faults such as ISC and lithium plating, and often relies heavily on complex feature engineering to extract key diagnostic features [105]. For example, Liu et al. [75] proposed an RF-based online detection and positioning method for monitoring ISC faulty batteries in LIB ESSs. By employing specialized feature extraction techniques to process voltage and current signals, the method significantly reduced the number of sensors required. The extracted features were then processed using RF, which helped to reduce both detection and localization time. In addition, RF can assess feature importance by calculating the contribution of each feature within individual decision trees and then averaging these contributions across the entire model, thereby enabling a comparative evaluation of feature significance. Zhu et al. [76] proposed an RF-based intelligent detection and early warning method for lithium deposition in LIBs. A tailored feature extraction approach was developed to capture deposition-related characteristics, while RF was employed to evaluate feature importance and identify key indicators, enabling effective detection and prediction. Although the reported accuracy reached 97.2 %, the limited dataset of only 24 samples raises concerns about the reliability of the results.

Although RF has achieved some success in fault diagnosis, it still faces some challenges. RF is well-suited for detecting slowly evolving faults in the time domain but exhibit limitations in handling rapid fault events. This is primarily due to two factors. First, the ensemble learning mechanism of RF is more effective at capturing subtle and gradual changes in time-series data, rather than abrupt and transient variations. Second, its strong dependence on feature engineering and labelled data may introduce latency, thereby constraining their responsiveness to fast-occurring faults. In addition, the lack of high-quality, large-scale battery fault data, which is crucial for RF training, further limits its performance.

3.1.3. Artificial neural network

ANN is one of the most widely used AI frameworks, capable of addressing a broad range of tasks [77]. It is a computational model inspired by the biological nervous system, designed to handle complex pattern recognition and learning problems. Typically consisting of an input layer, hidden layers, and an output layer, each neuron processes weighted inputs through an activation function, while connection weights are optimized via backpropagation to minimize prediction errors. Owing to its flexible architecture, ANN can be adapted for classification, regression, feature extraction, and time-series forecasting, demonstrating strong applicability across diverse domains. As a nonlinear network of interconnected simple units, ANN is well-suited to capture the intricate nonlinear relationships present in battery data, thereby enabling more accurate fault diagnosis [78]. Moreover, by modifying its structural composition, various ANN variants can be developed to target different fault detection tasks, including the identification of both fast and slow faults. The main ones commonly used for battery fault diagnosis are classical neural networks, long short-term memory (LSTM) neural networks, recurrent neural networks (RNN), convolutional neural networks (CNN), gated recurrent neural networks (GRNN) and extensions and combinations of these techniques [105]. Due to their strong sensitivity to temporal anomalies and their ability to model state evolution in real time, time-series modeling networks such as LSTM, RNN, and GRNN are frequently employed for the detection and prediction of fast-evolving faults, including thermal runaway, ESC, and overcharging. For example, Sun et al. [79] employed a CNN-LSTM model to predict battery voltage and evaluated the predicted values using correlation analysis, thereby enabling accurate detection of connection and ESC faults. Li et al. [80] proposed a hierarchical quantitative fault diagnosis method that integrates Mahalanobis distance with LSTM networks. The Mahalanobis distance, extracted from constant-current charging voltage curves, was used to capture charging platform hysteresis and reduced sequential voltage differences. A two-layer LSTM network was then applied to perform hierarchical diagnosis of continuous minor short-circuit faults. Although the method requires considerable computational resources, it achieved a detection accuracy of over 99 %. In addition, due to their capability to track gradual changes in fault states, these time-series modeling neural networks can also be applied to the modeling and diagnosis of slow-evolving faults. Zhao et al. [81] developed a voltage anomaly detection method based on GRNN with incremental training. Specifically, they proposed a GRNN combined with a multi-step-ahead prediction scheme to construct a voltage prediction model. This model enabled accurate detection of slowly evolving battery faults, such as slight overvoltage, undervoltage, and inconsistency issues.

CNNs are commonly employed to analyze sensor signals that have been transformed into time-frequency plots or other two-dimensional representations, enabling automatic extraction of fault features. When combined with other neural network models, CNNs can effectively detect a wide range of faults, including ISC faults and provide early warnings for thermal runaway [82,83]. In addition, recent studies have employed attention-based Transformer models for battery fault diagnosis. These models can capture early warning signals across multiple spatiotemporal scales, thereby enhancing the ability to predict the evolution of slow-developing faults effectively. For example, Zhao et al. [84] developed a Transformer-based architecture for battery fault detection and prediction using EV field data. The model achieved 96 % accuracy in identifying anomalies and forecasting failures 24 h to 7 days in advance, highlighting the potential of this approach. However, its high data demands and training time of several hours remain concerns.

In summary, a well-trained artificial neural network (ANN) model can effectively diagnose both fast-evolving and slow-developing battery faults. Emerging ANN technologies, such as physics-informed neural network (PINN), hold the potential to further advance fault diagnosis. However, However, limitations remain in the application of ANN. First, it requires a large amount of high-quality fault data for training, but such data is currently scarce and difficult to obtain. Additionally, ANN models demand significant computational power and memory for training and storing model parameters, which limits their application in low-cost devices.

3.2. Unsupervised learning

Unsupervised learning is an AI training approach that does not rely on labelled data but instead aims to uncover underlying structures or patterns from unlabelled input data [85]. Its independence from labelled datasets makes it particularly suitable for battery fault diagnosis, where high-quality fault data is often scarce. The commonly used algorithms for unsupervised learning in battery fault diagnosis are: clustering algorithms, outlier detection algorithms, and autoencoder (AE).

3.2.1. Clustering algorithms

Clustering algorithms are an unsupervised learning approach, making them well suited for real-world scenarios where such labels are unavailable or difficult to obtain. By grouping battery operating data according to feature similarity, these algorithms can uncover abnormal patterns and facilitate fault condition identification. In particular, clustering can be employed to establish characteristic groups that represent normal operating states. New observations that deviate substantially from these groups are regarded as anomalies, thereby enabling early detection of both sudden and progressive faults [86,87]. The clustering algorithms commonly used for battery fault diagnosis are K-means (partition-based clustering) and Density-Based Spatial Clustering of Applications with Noise (DBSCAN). For instance, Liu et al. [88] developed an online diagnosis and prediction method for abnormal voltage fluctuation faults based on the improved K-means method. Specifically, two-dimensional fault features that effectively identify voltage fluctuations were first extracted. Then, the faulty battery was identified using the enhanced K-means method. It is worth noting that the hyperparameters of the algorithm are optimized using a data-driven approach to improve clustering accuracy, although this may lead to increased algorithmic complexity. Compared with the K-means algorithm, DBSCAN has been more widely used in the field of battery fault diagnosis due to its extremely small requirements on hyperparameters, strong robustness to cluster shape [89]. Li et al. [90] developed a fault diagnosis method based on signal decomposition and DBSCAN-based two-dimensional feature clustering. Li et al. [91] proposed a DBSCAN-based fault diagnosis method using incremental capacity curves for detecting long-term potential faults in electric vehicles. The method can identify anomalies effectively, but its computation time of 2.8 s per sample restricts practical use. In addition, DBSCAN's reliance on Euclidean distance leads to degraded clustering performance in high-dimensional data, limiting its applicability to battery operation analysis.

Although clustering algorithms provide advantages in adaptive and unsupervised learning for battery fault diagnosis by uncovering potential fault modes and anomalies, their limitations are evident. They are highly sensitive to noise, require prior specification of the number of clusters, and perform poorly when handling time-series data or complex nonlinear fault modes. In practical applications, these shortcomings are often addressed by combining clustering with other diagnostic methods, such as signal processing approaches, to improve the accuracy and reliability of battery fault diagnosis.

3.2.2. Outlier detection algorithms

Outlier detection algorithms identify data points whose feature distributions deviate significantly from the majority of samples. Widely applied in unsupervised fault diagnosis, they are capable of detecting potential abnormalities or early indicators of failure. These algorithms generally rely on statistical characteristics, distance metrics, or density-based principles to distinguish data that diverges from normal patterns, thereby enabling timely detection of system anomalies. In the context of battery fault diagnosis, by monitoring key parameters such as voltage, temperature, and capacity, and extracting representative features, outlier detection can promptly identify abnormal changes. This facilitates the detection of faults such as ISC, overcharge, and over-discharge. The outlier detection algorithms commonly used in fault diagnosis include isolation forest, local outlier factor (LOF) algorithm, and its variants [92]. For example, Jiang et al. [93] developed a battery fault diagnosis method based on the isolation forest algorithm, which demonstrated strong detection capabilities for both progressive and sudden faults. Specifically, the original voltage data were first processed and decomposed into a static component, which is highly correlated with aging inconsistency, and a dynamic component, which reflects abnormal information. The characteristic parameters of both components were then extracted and input into the isolation forest algorithm for anomaly detection, enabling the identification of faulty batteries. Similarly, Wu et al. [94] used the improved kurtosis index to extract the weak abnormal features of batteries and then used the isolation forest algorithm to detect faulty batteries. In addition, fault diagnosis using LOF has also been widely studied [95,96]. For example, Wang et al. [97] proposed a multi-fault diagnosis strategy based on multi-feature fusion and LOF, employing a three-layer framework of voltage limit frequency, multi-feature cross-verification, and LOF to identify fault type and severity. Threshold adjustment eliminates missed alarms but leads to a high false alarm rate. The method processes one minute of data in just 0.043 s, demonstrating excellent computational efficiency. However, it is more effective for sudden faults with distinct features, while its ability to detect slow-evolving faults remains limited.

In summary, the outlier monitoring method offers high flexibility and ease of implementation. However, it heavily depends on expert knowledge for fault feature extraction and faces challenges in handling high-dimensional data. Consequently, it is often combined with other techniques to achieve improved fault diagnosis accuracy.

3.2.3. Autoencoder

As shown in Fig. 7, AE is an unsupervised neural network model consisting of an encoder and a decoder. The encoder compresses the input data into a low-dimensional representation, while the decoder reconstructs it to its original form, thereby effectively capturing the key features of the data. In fault diagnosis, the model identifies system anomalies and potential faults by detecting significant changes in reconstruction errors. The general process of using AE for battery fault diagnosis is as follows. By learning the data patterns of the battery in its normal state, the AE can extract low-dimensional feature representations of the data and then reconstruct the input data [98]. When a fault occurs, the characteristics of the input data significantly deviate from the normal state distribution, resulting in an increase in the reconstruction error of the AE. By monitoring changes in reconstruction errors and adaptively adjusting the network architecture based on fault characteristics, AEs exhibit strong temporal adaptability and can effectively detect both rapid and slowly evolving faults [99,100]. For example, Wang et al. [101] proposed a battery fault diagnosis framework based on temporal convolutional AE, which can quickly and accurately identify abnormal power batteries by evaluating the reconstruction error. Zhang et al. [102] integrated a neural network with an interpretable module into the AE framework and proposed a fault diagnosis method adaptable to different vehicle platforms. The approach effectively detects inconsistency and overvoltage faults with up to 94 % accuracy, but requires over 4 s for recognition. In addition, some studies have used AEs for feature extraction and combined them with other methods to complete fault diagnosis [103]. For instance, Jiang et al. [104] utilized the dimensionality reduction capability of sparse AEs to extract representative features related to battery faults, and then combined these features with the discrete Fréchet distance to enable fault detection. This approach effectively reduces the dependence on expert knowledge inherent in traditional feature engineering.

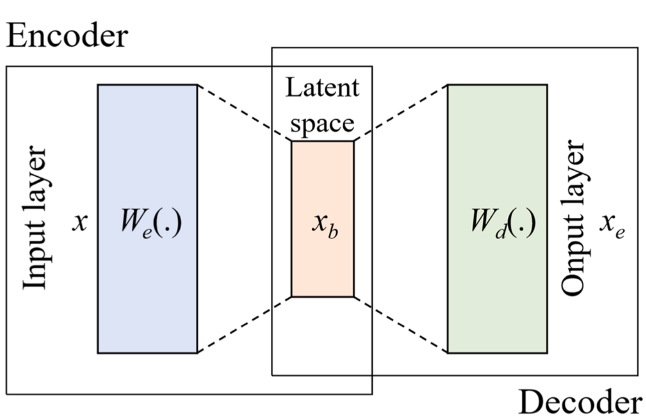

Fig. 7. The basic structure of AE.

In summary, AEs offer the advantage of integrating various neural network architectures (such as LSTM or CNN) to accurately capture the temporal and nonlinear characteristics of LIBs, while eliminating the need for fault samples during model training, thereby enhancing its practical applicability. However, they also face inherent limitations common to ANN, including the requirement for substantial computing resources and challenges in selecting optimal hyperparameters.

3.3. Semi-supervised learning

Semi-supervised learning is a hybrid approach that integrates the advantages of both supervised and unsupervised learning. By leveraging a small amount of labelled data together with a large amount of unlabelled data, it can improve model performance while reducing the cost and effort of data labelling. This approach enhances both the generalization ability and the learning efficiency of the model. In battery fault diagnosis, semi-supervised learning is particularly valuable when labelled fault data is scarce, as it enables the model to exploit information from both labelled and unlabelled samples to improve fault detection accuracy. Moreover, it can construct fault models from limited samples and generate additional fault data to support model training [105]. Commonly used semi-supervised learning algorithms in this field include generative adversarial network (GAN) and variational autoencoder (VAE).

3.3.1. Generative adversarial networks

GAN is a deep learning framework composed of two neural networks: the generator and the discriminator. The generator is responsible for producing data samples that closely resemble real data, while the discriminator evaluates whether a given sample is authentic or generated. Through adversarial training, the two networks compete and evolve simultaneously: the generator continuously improves its ability to create realistic samples capable of deceiving the discriminator, whereas the discriminator enhances its capability to accurately distinguish between real and synthetic data [106,107]. In fault diagnosis, GAN can be used to generate battery data under different fault conditions, particularly when fault data is scarce. By generating fault samples and training the diagnosis model alongside real data, the model's robustness can be enhanced, and its ability to recognize unknown fault modes can be improved [108,109]. For example, to address the issue where the fault occurrence time is much shorter than the normal operating time, resulting in a disproportionately small amount of fault data and a lack of diverse fault features, Fang et al. [110] proposed a data enhancement method based on the least squares generative adversarial network (LSGAN). This method first trained the original power battery fault dataset using the LSGAN model to generate diverse sample data representing various fault states. The enhanced dataset was then used to develop a voltage fault diagnosis algorithm. Experimental results showed that after the dataset enhancement, the performance of the fault diagnosis algorithm was significantly improved. Similarly, Zhao et al. [111] used auxiliary training samples generated from distributions similar to, but different from, the real samples, and then developed a regression model based on these samples to predict battery capacity and detect abnormal capacity decay. However, it is important to note that the GAN-based data generation process relies on learning data distributions rather than physical modeling, which makes it susceptible to producing "pseudo-fault data" lacking electrochemical validity. Such data may lead the model to learn unrepresentative fault features, thereby compromising the reliability of fault diagnosis. In addition, some studies used GAN-generated data as a reference to compare with real data to detect faults. For instance, Heng et al. [112] proposed a GAN-based battery thermal runaway prediction method. This method used GAN-generated data as the reference normal curve of the original battery charging process to detect potential anomalies. But the difficult process of training GAN raises concerns about its practicality.

In summary, existing research shows that GAN can enhance battery fault diagnosis by generating fault or reference samples, thereby improving the performance of diagnostic models. However, they also face challenges such as high computational complexity and an unstable training process, which makes them susceptible to issues like mode collapse.

3.3.2. *Variational autoencoder*

VAE is a generative model that combines the concepts of AEs and variational inference. Specifically, it introduces variational inference into the AE framework, allowing the model to learn the underlying distribution of the data. By incorporating randomness in the latent space, VAE enables the generation of new samples and supports interpolation and other operations within the latent space [113]. Similar to AE, VAE can also use reconstruction errors for fault detection, but the reconstruction method is different. Specifically, VAE introduces a probability distribution (usually a Gaussian distribution) during the encoding process, thereby generating more diverse samples that are not included in the training data, increasing the versatility of the fault diagnosis algorithm [114]. For example, Sun et al. [115] used VAE based on GRU for power battery pack anomaly detection. Specifically, GRU was employed to capture the complex temporal dependencies in the multivariate time series of the battery, while VAE was used to probabilistically reconstruct the input samples. The peak over-threshold model, based on classical extreme value theory, was applied to set a reasonable anomaly detection threshold. Finally, the reconstruction error was compared to this threshold to detect faults.

However, although these researchers applied VAE for fault diagnosis, VAE, similar to GAN, also faces the challenge of a complex training process. This process often requires a long training time, particularly when dealing with large datasets.

In summary, Section 3 classified the applications of AI technologies in battery fault diagnosis and provided a comparative analysis of the advantages, limitations, and applicable scenarios of supervised, unsupervised, and semi-supervised approaches, as shown in Table 2. However, the reliance of these methods on conventional voltage and current data imposes inherent constraints, as such signals often lack sufficient sensitivity to capture early or subtle fault features. To overcome these limitations, Section 4 will explore the integration of AI with advanced sensing technologies, which provides richer multidimensional information and offers new opportunities to enhance the accuracy and robustness of battery fault diagnosis.

Table 2
Comparison of AI-based LIB fault diagnosis methods.

Diagnostic methods	Main advantages	Main limitations	Ref
SVM	• Capable of capturing the nonlinearity of LIBs. • Less complex modeling compared to ANN.	• Data preprocessing is time-consuming and complex. • Kernel function and parameter tuning are challenging. • Not suitable for processing large-scale data.	[32, 68]
RF	• High classification ability. • Low computational complexity.	• Lack of ability to detect rapid failures. • Need a large amount of high-quality battery failure data.	[73]
ANN	• High precision. • Highly capable of capturing the nonlinearity of LIBs. • Capable of processing large amounts of data.	• High-quality, large-volume battery fault data is needed. • Complex modeling and high computational complexity. • Training takes a long time.	[76, 77]
Clustering algorithms	• No reliance on labelled data. • Easy to implement.	• Sensitive to initial conditions. • Difficult to handle time series data and complex nonlinear failure modes.	[83, 84]
Outlier detection algorithms	• No reliance on labelled data. • High flexibility. • Easy to implement.	• Requires certain expertise. • Difficulty handling high-dimensional data.	[92]
AE	• No reliance on labelled data. • Capable of capturing the nonlinearity of LIBs.	• Requires a lot of computing resources. • Difficulty in selecting network structure and hyperparameters.	[96, 97]
GAN	• Strong generalization ability. • Implement classification and regression tasks when labelled data is insufficient.	• Unstable training process. • High computational complexity.	[103, 104]
VAE	• No reliance on labelled data. • New fault samples can be generated.	• Complex training process. • Generated data does not adequately cover all types of faults.	[110]

4. Senor fusion-enhanced battery fault diagnosis

Battery sensing and fault detection are inherently interconnected, forming the foundation for intelligent monitoring and precise diagnosis. Reliable fault identification requires comprehensive monitoring of the battery's operational states. Beyond voltage and current, sensors can provide diverse physical measurements—such as temperature, mechanical stress, gas concentration, and acoustic emissions—that supply the raw data for anomaly detection, feature extraction, and fault pattern recognition. Broader and deeper sensing coverage generally reduces diagnostic complexity while improving detection accuracy. As discussed in the previous section, existing AI-based diagnostic approaches remain constrained by the limited information carried in electrical and thermal signals, which may exhibit slow response times and overlapping fault characteristics [27]. To address these shortcomings, it is necessary to leverage advanced sensing instruments capable of probing a wider range of internal multi-physical states. As illustrated in Fig. 8, commonly employed advanced sensors include electrochemical impedance spectroscopy (EIS), fiber optic sensors, ultrasonic detectors, and other high-resolution instruments [31].

4.1. *Electrochemical impedance spectroscopy*

EIS is a non-destructive diagnostic technique used to analyze electrochemical processes in batteries. By applying a small-amplitude AC signal and measuring the corresponding voltage response across different frequencies, it characterizes the battery's impedance spectrum. The obtained impedance data provide insights into the internal electrochemical dynamics and electrode interface structure, serving as a reliable indicator of the battery state. When internal faults occur, the EIS response exhibits distinct variations. By integrating AI algorithms, these variations can be effectively correlated with specific fault types, making EIS a powerful tool for battery fault diagnosis [116]. For example, Cui et al. [117] developed an early ISC fault detection method by combining EIS with deep neural networks (DNN), achieving a detection accuracy of

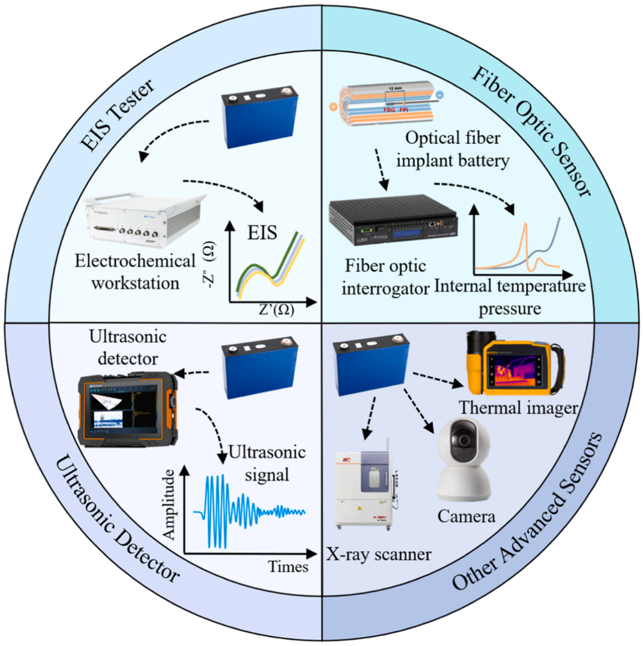

Fig. 8. Advanced sensor devices used in battery fault diagnosis in existing research.

97.5 %. Fig. 9 shows the process of this EIS-based battery ISC fault diagnosis framework. Specifically, they labelled the EIS data of normal batteries as 0 and the EIS data of ISC-affected batteries as 1, and then trained the DNN to identify ISC faults. Additionally, to reduce the required EIS measurement time and improve computational efficiency, the study analyzed the relationship between EIS and ISC faults using relaxation time distribution and sensitivity methods. It then selected the frequency band most sensitive to ISC for fault detection. The results demonstrated that, while maintaining high detection accuracy, the detection speed was significantly improved. Zhang et al. [118] proposed a method for diagnosing electrolyte leakage faults using EIS tests based on SVM. First, the distribution relaxation time (DRT) method was employed to analyze the impact of leakage on the dynamic reaction process of both full and half cells. Then, features were extracted from the EIS and DRT curves and fed into the SVM for electrolyte leakage fault detection. Zhu et al. [119] achieved the evaluation of battery inconsistency by using LOF to detect abnormal characteristic frequency points in EIS. What's more, Zhang et al. [120] used EIS to detect battery lithium plating faults. In addition, since the impedance spectrum can reflect the internal temperature and structural changes of the battery, it is also used in thermal runaway warning systems [121]. Li et al. [122] used the RReliefF algorithm to extract the key features of thermal runaway from EIS data and analyzed the thermal runaway mechanism associated with specific frequencies. Based on the extracted features, they further developed a three-level early warning strategy for single cells, series modules, and parallel modules. Under thermal abuse conditions, this method was able to successfully issue an early warning signal before the battery's self-heating temperature was reached. In summary, EIS demonstrates high sensitivity to various faults, enabling non-destructive detection, and holds significant potential for battery fault diagnosis.

Notably, although EIS provides rich information about the internal state of the battery and greatly supports fault diagnosis, its acquisition remains challenging. Typically, measuring battery EIS requires specialized equipment to perform sinusoidal scanning under controlled laboratory conditions. in-vehicle applications, the application of impedance spectroscopy is restricted by the limited accuracy of excitation generators, low sampling frequencies, and long acquisition times, which hinder its practical implementation. In this context, AI technology offers effective support for obtaining and utilizing EIS in real-world scenarios. For example, Chang et al. [123] proposed a new method to obtain the impedance spectrum using LSTM. This method utilized the impedance

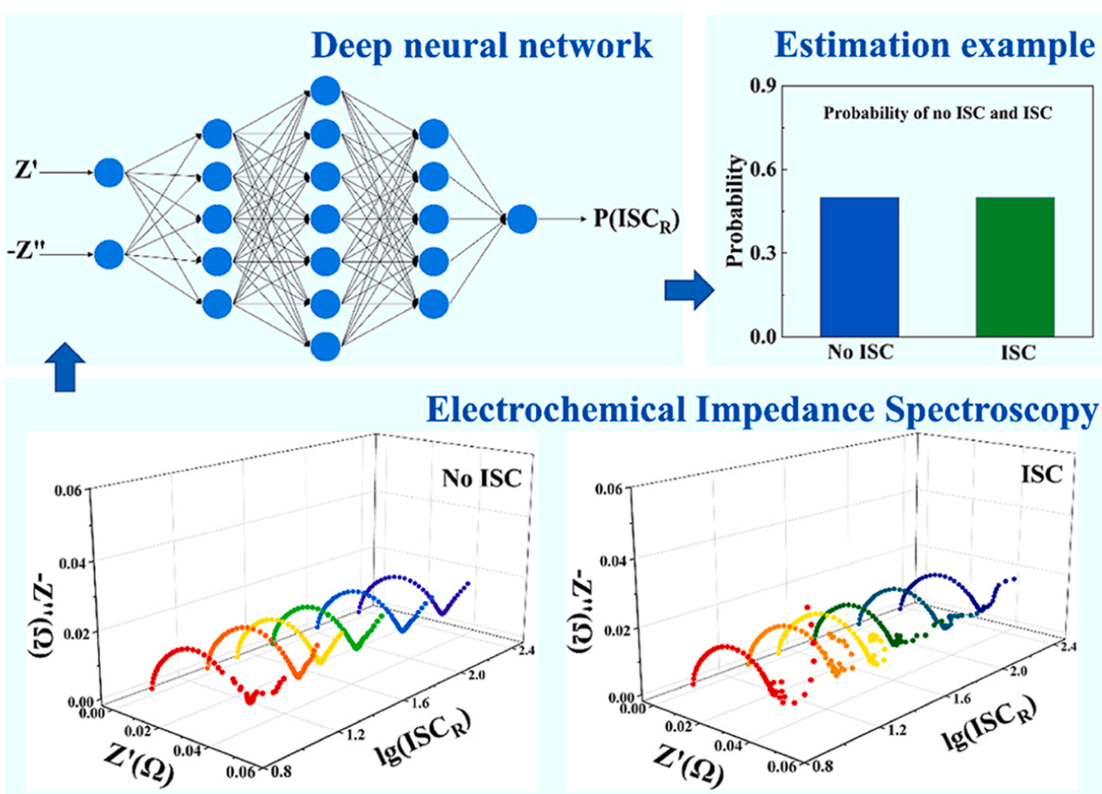

Fig. 9. Schematic diagram of ISC fault early detection method [117].

measured at several characteristic frequencies as input to estimate the complete impedance spectrum, significantly reducing the measurement time. The process of estimating the complete EIS is shown in Fig. 10. First, impedance fragments at specific frequencies in the EIS were selected as features using DRT. Then, the complete impedance spectrum was reconstructed using the LSTM neural network model, with the model's hyperparameters optimized through a population optimization algorithm. Similarly, Tang et al. [124] combined the fractional-order circuit model and the median filter neural network method to predict the complete impedance spectrum using only a partial EIS fragment. In summary, these AI methods are beneficial for obtaining EIS at a lower cost and in a shorter time, thereby promoting the practical application of fault diagnosis algorithms using EIS.

4.2. Fiber optic sensor

Fiber optic sensors, characterized by high sensitivity, immunity to electromagnetic interference, corrosion resistance, and miniaturization, provide distinct advantages for battery monitoring. They can accurately detect temperature, stress, and physical changes within the battery, which are critical for understanding degradation processes. These sensors play a vital role in state estimation and fault diagnosis, offering valuable data to support the development of more accurate diagnostic methods [125,126]. For example, Rente et al. [127] developed a real-time SOC estimator based on signals obtained from a fiber Bragg grating (FBG) sensor system by fitting strain data with SOC data based on a machine learning dynamic time warping algorithm.

Currently, the most common application of optical fibers in the field of fault diagnosis is the exploration of thermal runaway mechanisms and early warning [128,129]. For example, as shown in Fig.11, Mei et al. [130] developed a compact multifunctional fiber optic sensor that can be inserted into a commercial 18,650 battery to continuously monitor the internal temperature and pressure during battery thermal runaway. They found a stable and repeatable correlation between the battery's thermal runaway and the optical response. Specifically, two distinct peaks in the pressure signal from the optical fiber correspond to safe exhaust and the onset of thermal runaway. This correlation enables early warning of thermal runaway, demonstrating the feasibility of using fiber optics to predict such failures. Furthermore, Chen et al. [131] proposed a method for estimating the internal temperature during thermal runaway of LIBs by combining optical fiber sensing and deep learning. Specifically, they implanted FBG sensors in the battery to monitor both the temperature and strain on the battery surface and at the three-dimensional center during the entire thermal runaway experiment. Based on the experimental data, they developed a two-layer LSTM model integrated with Bayesian optimization to estimate the internal temperature, which is difficult to measure directly, by monitoring easily measurable characteristic parameters. In addition, some studies have used fiber optic sensors to monitor thermal runaway-related gases for early warning purposes [132,133].

In summary, these studies have demonstrated that fiber optic sensors can play a significant role in fault diagnosis, particularly in thermal runaway mechanism research and early warning, by providing precise insights into the battery's state, especially when implanted inside the battery. However, fiber optic sensors also present several limitations. First, their deployment is costly, and the implantation process may cause structural damage that compromises battery performance. This was demonstrated in a study by Guo et al. [134], which showed that improper implantation can significantly reduce battery cycle life. Specifically, while batteries without implants retained 90.9 % of their capacity after 50 cycles, those embedded with fiber optics exhibited a minimum capacity retention of only 77.5 % after the same number of cycles. Additionally, current research has primarily focused on thermal runaway, with further development needed for diagnosing other fault types, such as ISC and lithium plating. Finally, while the data obtained through fiber optic sensors has great potential, it has not yet been systematically integrated with AI technology for fault diagnosis, which could significantly enhance the performance of diagnostic algorithms.

4.3. Ultrasonic detector

Ultrasonic testing is one of the most widely used and fastest-growing non-destructive testing technologies [135]. It is highly sensitive to changes in the internal structure and mechanical properties of the test object and is very suitable for detecting the internal state of the battery. For example, Liu et al. [136] developed a battery state of health (SOH) estimation method based on ultrasonic technology, achieving satisfactory accuracy. Fig. 12 is a schematic diagram of ultrasonic testing of a battery. This ability to detect internal states makes it highly suitable for battery fault diagnosis as well. Currently, the application of ultrasonic technology in battery fault detection primarily includes the identification of internal defects during battery manufacturing, detection of lithium plating, and monitoring of thermal runaway. For instance, Bauermann et al. [137] used ultrasonic testing technology to detect internal defects of button cells and pouch cells and performed visual characterization. Xie et al. [138] used ultrasonic detection technology to detect the lithium plating process that accompanies battery aging. The aforementioned ultrasonic detection research on internal defects and

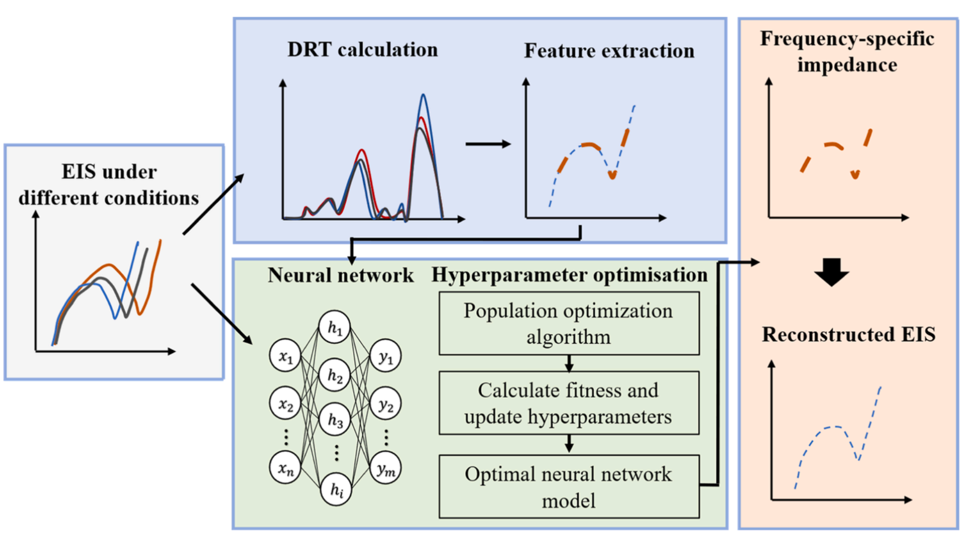

Fig. 10. Process for reconstructing a complete impedance spectrum from a limited number of frequency points using a neural network.

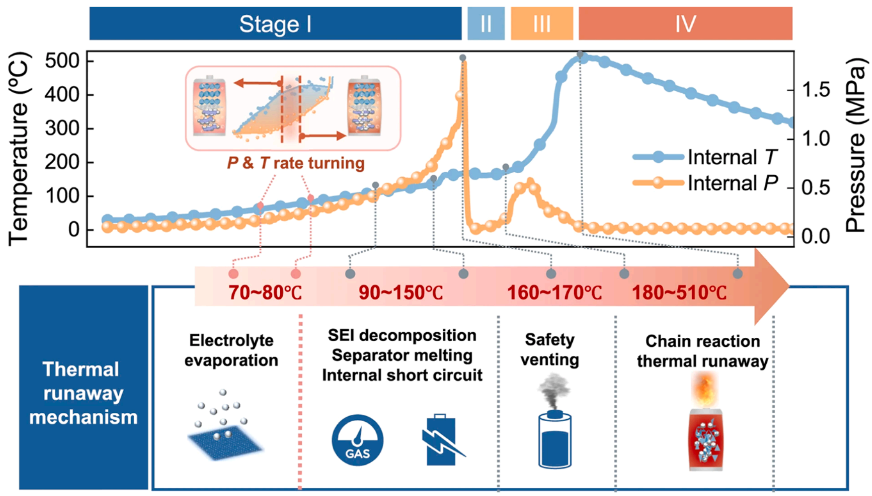

Fig. 11. Optical fiber is used to detect the internal temperature and stress of the battery to establish a corresponding relationship with thermal runaway [130].

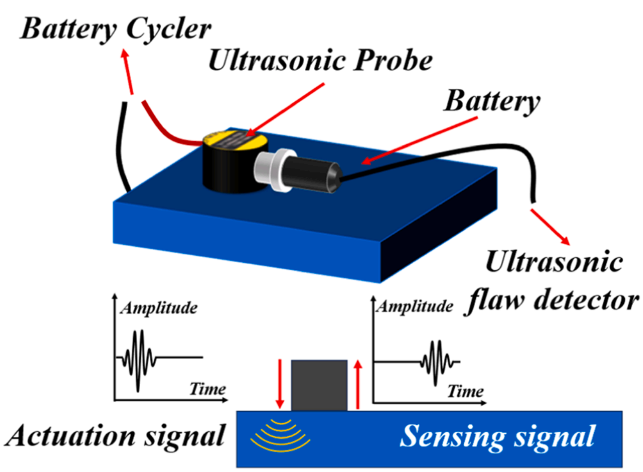

Fig. 12. Illustration of battery ultrasonic wave detection.

lithium plating in batteries largely relies on manual feature extraction and analysis. This reliance limits its ability to qualitatively analyze defect types and accurately locate faults. Integrating AI technology for in-depth analysis of ultrasonic signals offers a promising solution to these challenges.

In the realm of thermal runaway warning, several studies have combined AI techniques with ultrasonic sensors to estimate the internal temperature of batteries, enhancing the precision and effectiveness of fault detection and prevention [139,140]. For example, Zhang et al. [141] proposed a joint estimation method of SOC and temperature of a lithium iron phosphate battery based on ultrasonic reflection wave. Specifically, the characteristic index extraction interval for the battery state was determined through sliding window matching correlation analysis. Virtual samples were generated to augment the data after feature extraction. Finally, a back propagation (BP) neural network model was employed for the joint estimation of the battery's multi-state parameters across a wide temperature range. In summary, these studies highlight the significant potential of non-destructive ultrasonic testing technology in battery fault diagnosis. However, some challenges remain, particularly the need for advanced techniques to acquire and analyze ultrasonic data. AI technology holds promise in addressing these challenges and enhancing the effectiveness of ultrasonic testing in fault diagnosis.

4.4. Other devices

There are other advanced sensing technologies that can be used for battery safety monitoring and fault detection, including optical monitoring technology [142], electrode potential sensors [143], gas sensors [144], infrared thermal imaging technology [145], sound sensors [146], X-ray scanning technology [147], CT scanning technology [148]. Among these technologies, optical monitoring is the one most closely integrated with AI for fault detection. Optical monitoring methods often combine computer vision and AI to analyze optical images captured by cameras. These techniques have been widely used to detect battery faults during the production process. Din et al. [149] achieved automatic detection of faults in the battery manufacturing process by using image processing and AI techniques. Fig.13 is a fault detection flowchart of the proposed method. First, a CNN was employed to extract features from the image data. To address the issue of data imbalance and prevent model overfitting, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to augment the dataset. Subsequently, various machine learning and deep learning models were trained using the CNN-extracted features and the oversampled data to detect and classify faults in the battery manufacturing process. However, the achieved detection accuracy was approximately 84 %, which remains insufficient for practical application and requires further enhancement. Yang et al. [150] focused on the defects in laser welding, a critical process in battery manufacturing, and developed a defect classification and quality inspection method based on a deep learning model, specifically the visual geometry group (VGG) network. These studies show that optical inspection technology has great potential in anomaly detection in battery manufacturing, but the performance still needs to be further improved to meet practical needs. Additionally, in recent years, optical monitoring methods have been explored for safety monitoring during battery operation. Ma et al. [151] designed a sequential transformer thermal warning system based on battery thermal images. The results showed that the method had good recognition and warning performance under various external lighting conditions.

Electrode potential sensors are highly valuable for directly monitoring the internal state of batteries and for identifying lithium plating and ISC failures. For example, electrode potential sensors incorporate a reference electrode (RE) into the battery system, forming a three-electrode configuration together with the working electrode (WE) and counter electrode (CE). This structure enables the independent measurement of each electrode's potential, rather than relying solely on the overall cell voltage, thereby providing an effective tool for in-situ diagnostics. For instance, Su et al. [152] embedded potential sensing materials directly into the battery separator, creating a stable reference

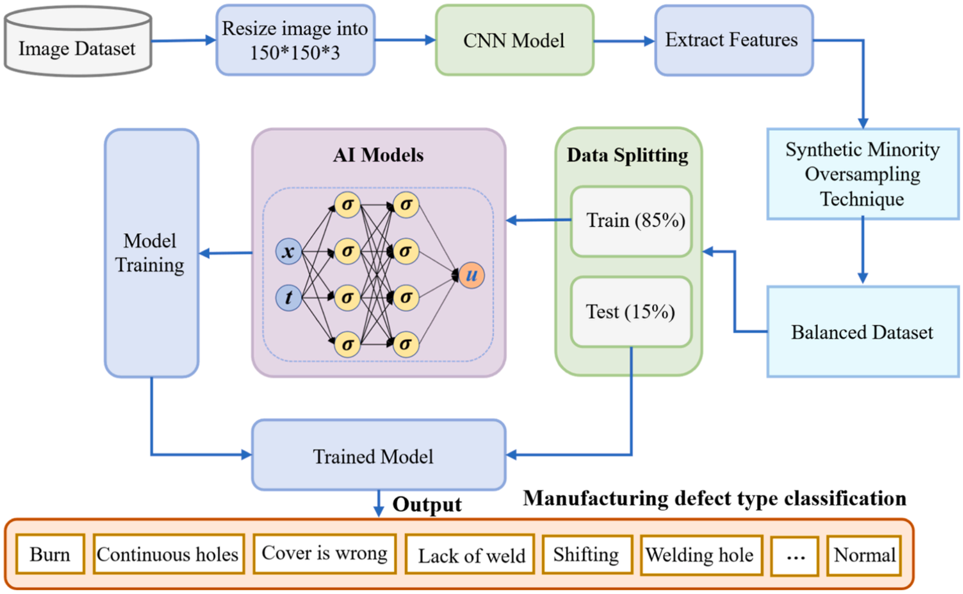

Fig. 13. Battery manufacturing fault detection process based on visual images [149].

potential and serving as a sensing terminal for in-situ monitoring of the negative electrode potential. This configuration allowed for the identification of severe side reactions and abnormal lithium deposition behavior. Moreover, such potential-sensing separators can detect pre-existing or developing internal defects at an early stage—faults that are often difficult to identify through external battery characteristics. However, current reference electrodes suffer from limited long-term stability under harsh electrolyte conditions, and their spatial positioning within the cell significantly influences measurement accuracy.

Gas signal sensing plays a critical role in diagnosing failures in LIBs, particularly during thermal runaway, by monitoring the dynamics of gas generation caused by electrolyte decomposition and internal structural degradation [153]. The detection of flammable and toxic gases—such as CO_2, CO, and various hydrocarbons—serves as a sensitive indicator of electrochemical side reactions, internal pressure accumulation, and potential electrolyte leakage. Unlike other sensing methods, gas signal detection captures the chemical evolution and volumetric changes within sealed cells, offering early diagnostic insights into fault initiation

Table 3
Comparative study of advanced sensor technology combined with AI in battery fault diagnosis.

Diagnostic methods	Main advantages	Main limitations	Applicable Scenarios	Detection accuracy
EIS	• Non-destructive. • High fault sensitivity. • Suitable for diagnosis of various types of battery faults.	• Complex and time-consuming testing process. • High requirements for professional analysis algorithms. • Susceptible to environmental conditions.	Overcharge, over-discharge, lithium deposition, ISC and thermal runaway detection.	High precision in the laboratory, but easily affected by temperature in practice.
Fiber optic sensor	• Directly detect the internal status of the battery. • High precision and high sensitivity. • Simultaneous monitoring of multiple parameters.	• High deployment cost. • Complex data processing. • Difficult maintenance.	Thermal runaway detection.	High precision and extremely sensitive to stress, temperature and local state changes.
Ultrasonic detector	• Non-destructive. • Real-time monitoring. • High sensitivity.	• Implementation and data analysis require a high level of technical skills. • High deployment cost. • The stability of the coupling medium needs to be considered.	Internal temperature estimation, internal defect detection, thermal runaway warning.	Generally, it is greatly affected by test conditions.
Optical monitoring technology	• Non-destructive. • Low cost and strong scalability.	• Can only detect obvious defects on the surface.	Battery defect detection during production.	Medium, must have obvious characteristics, such as cracks and fire.
Electrode potential sensor	• The real potential difference of the monomer/electrode can be directly obtained.	• Highly disruptive. • Difficult to integrate and poor stability. • High cost	ISC, lithium plating.	High, directly monitor the internal status of the battery.
Gas sensor	• High sensitivity, good early warning capability for heat-related faults • Lower cost.	• Unable to distinguish specific failure mechanisms. • Susceptible to environmental interference.	Thermal runaway, overcharging.	High, affected by sensor performance.
Infrared thermal imaging technology	• Non-contact detection • Fast detection speed. • Lower cost.	• Can only monitor surface temperature.	Thermal runaway.	High, but can only detect faults that have developed to a certain extent

prior to catastrophic failure [154]. In summary, gas signals can serve as an effective early warning indicator for battery thermal runaway, typically providing a lead time of several minutes to nearly ten minutes before the onset of thermal events. This early detection enables timely intervention and ensures the safe evacuation of personnel. However, by the time gas generation becomes detectable, the battery system has often already undergone irreversible internal damage.

Infrared thermal imaging technology reconstructs the temperature distribution of batteries by capturing their emitted thermal radiation, offering valuable insights for fault detection. For example, Kim et al. [155] utilized this method on soft-pack lithium iron phosphate batteries under high-rate cycling, uncovering the rapid temperature rise behavior and assessing material degradation, which supported the optimization of component design. This technique provides high temporal and spatial resolution and a comprehensive view of thermal behavior. However, its measurement accuracy may be affected by factors such as calibration deviations, variations in surface emissivity, and environmental disturbances.

In summary, these advanced sensors enable multi-dimensional monitoring of battery conditions and reaction processes, offering valuable support for the development of fault diagnosis techniques. The latest progress in this area is introduced and a comparative study of these technologies is conducted in Table 3. However, their integration with AI remains limited, restricting their potential for deeper application in fault diagnosis and highlighting the need for further research.

5. Challenges and prospects

5.1. Existing problems

Sections 3 and 4 provide systematic discussions on AI-based fault detection/diagnosis methods for LIBs and the integration of AI with advanced sensing technologies, respectively. While significant progress has been made in applying AI and advanced sensors for battery fault diagnosis, several critical challenges still exist:

(1) Complexity of concurrent and overlapping fault signatures. In real-world battery operations, multiple failure mechanisms frequently coexist and interact in complex, nonlinear ways, producing signal patterns that are challenging to isolate and interpret. For instance, ISC faults can cause localized heating, accelerate electrolyte decomposition, induce lithium plating, and compromise separator integrity. Simultaneously, high-rate charging intensifies mechanical stress and promotes electrode delamination, generating thermal and electrical signatures that significantly overlap with those produced by ISCs or over-discharge conditions. Although several studies—such as those employing graph-based fault trees and digital twin simulations—have attempted to disentangle these coupled failure modes, most existing diagnostic algorithms are still developed under the assumption of a single-fault scenario. Moreover, they primarily rely on conventional signals such as voltage or surface temperature. Even advanced AI techniques struggle to distinguish co-evolving faults when limited to pack-level measurement data, due to both the similarity of observable characteristics (e.g., voltage drops, temperature increases) and the spatial averaging inherent in such sensing approaches. Addressing this challenge necessitates the collection of high-resolution, multi-dimensional data—such as electrochemical impedance, acoustic emissions, and infrared thermal profiles—and the development of AI architectures capable of fusing these heterogeneous signals. Additionally, incorporating physics-based constraints can enhance model interpretability and enable more accurate tracking of individual fault propagation paths.

(2) Scarcity and poor quality of realistic fault data. Data-driven AI models thrive on large, diverse datasets that accurately reflect the complexity of real-world failures. However, publicly available repositories predominantly contain normal cycling records or simplistic fault simulations such as paralleling resistors to mimic an ISC, which capture only a fraction of the electrochemical and mechanical dynamics at play. As a result, models trained on these datasets often overfit to spurious features and fail to generalize when confronted with genuine anomalies in the field. Controlled destructive testing to harvest authentic failure data is both costly and hazardous, further limiting dataset growth. Recent research has explored physics-guided GANs and reinforcement learning-based augmentation to synthesize more realistic fault patterns, but these methods still lack standard validation metrics and risk producing unphysical samples. Developing a robust data ecosystem will require coordinated efforts among academia, industry, and standardization bodies to curate open, high-fidelity fault libraries across multiple cell chemistries and aging stages. Complementary techniques—such as transfer learning from related domains and semi-supervised anomaly detection—can also help mitigate data scarcity by leveraging abundant healthy-state data.

(3) Engineering and integration barriers for advanced sensors. Advanced sensing technologies—such as EIS, FBGs, ultrasonic tomography, and X-ray CT—offer unprecedented visibility into internal battery phenomena. However, their integration into practical BMS applications remains limited. High-precision instrumentation often depends on bulky hardware and tightly controlled environments, which are incompatible with real-world deployment. For example, embedding fiber sensors may damage electrodes or separators, adversely affecting battery performance and potentially introducing diagnostic bias. Similarly, field-deployable EIS modules must balance measurement speed with frequency resolution, and ultrasonic systems require coupling media that may degrade under prolonged cycling. In addition to these technical concerns, several practical challenges must also be addressed. First, sensor calibration is a critical issue, as long-term drift and signal degradation can compromise diagnostic accuracy, especially for embedded or in situ devices. Second, cost constraints present a barrier to large-scale adoption, since many advanced sensing systems currently rely on expensive materials and fabrication processes. Third, real-time implementation poses difficulties, given that high-resolution measurements often require significant computational resources and may introduce delays in decision-making. Finally, robustness under extreme conditions—including wide temperature ranges, high currents, and aggressive chemical environments—remains insufficiently validated, raising questions about sensor durability and reliability in commercial operation. To bridge these gaps, future research should emphasize scalable sensor fabrication, cost-efficient design strategies, and robust packaging capable of enduring harsh electrochemical environments. Developing self-calibrating sensor networks that can maintain accuracy over extended operational lifespans will also be vital. Close collaboration between sensor designers and battery manufacturers is essential to ensure that next-generation sensing systems preserve cell integrity, support real-time monitoring, and remain compatible with existing BMS infrastructure. Such collaboration ultimately enables the large-scale deployment of advanced sensors in practical battery applications.

(4) Insufficient end-to-end multimodal fusion and interpretability. Although individual sensors can capture rich and diverse data streams, diagnostic workflows often treat each modality in isolation or depend heavily on manual interpretation. This fragmented approach limits the ability to uncover cross-modal correlations that may reveal early-stage failures. For instance, while thermal imaging might identify a hotspot, the absence of concurrent analysis with impedance variations or acoustic signals

leaves the root cause ambiguous. Moreover, many AI-based diagnostic models function as black boxes, offering limited transparency into their decision logic, which is a critical barrier for safety-sensitive applications. Recent attempts to integrate time-series models such as LSTM and Transformer with graph neural networks have demonstrated potential, yet they often lack standardized interpretability mechanisms or the incorporation of physics-informed constraints to ensure mechanical plausibility. Addressing these limitations requires the development of end-to-end architectures that can jointly process electrochemical, thermal, acoustic, and visual data streams. These architectures should be augmented by attention mechanisms and reasoning frameworks based on large language models to identify salient fault indicators. Embedding interpretability tools—such as counterfactual explanations or symbolic rule extraction—is essential not only for regulatory compliance but also for gaining user trust, ultimately enabling the deployment of intelligent, transparent, and dependable battery health management systems.

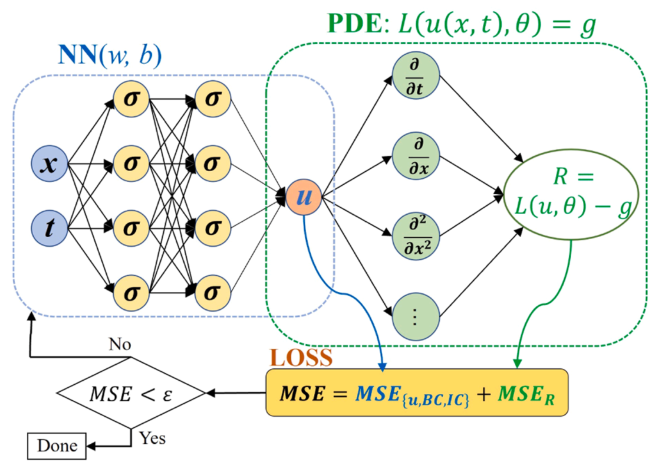

Fig. 15. The basic structure of PINN.

5.2. Future prospects

This paper investigates AI technology and advanced sensor technology, providing a systematic review of battery fault diagnosis methods that integrate AI with advanced sensors. It identifies current limitations and technical challenges, while offering insights into future development trends for intelligent battery fault diagnosis systems based on advanced sensor-AI integration. Fig. 14 shows the relationship between the above challenges and the opportunities that are expected to address them.

(1) AI technology is evolving rapidly, offering transformative opportunities for enhancing battery fault diagnosis. One promising direction is explainable AI, which addresses the longstanding challenge of interpreting the inner workings of deep neural networks. It has already been applied successfully in battery health state estimation and prediction tasks, providing greater transparency and confidence in decision-making [156]. For instance, Zhao et al. [157] demonstrated its utility in battery health management by offering interpretable outputs aligned with expert knowledge. Another emerging technique is PINN, which integrates physical constraints into neural network training by embedding governing equations into the loss function. As illustrated in Fig. 15, PINN enables accurate modeling even with sparse or noisy data, making it particularly suitable for battery scenarios where fault data is limited or costly to obtain. Beyond these, large language models (LLMs) represent a groundbreaking advancement with unique strengths in multimodal integration, cross-domain generalization, and contextual reasoning. LLMs can process and synthesize heterogeneous data types (text, time series, images, sensor streams) and infer complex relationships that conventional models may overlook. When combined with other AI architectures, LLMs have the potential to unify diverse diagnostic modalities and generate interpretable reasoning chains, paving the way for more generalized, transparent, and trustworthy battery fault diagnosis frameworks. Continued exploration and adaptation of such advanced AI technologies will be critical to ensuring the safety, reliability, and scalability of future battery systems.

(2) Effective integration of miniaturized, robust sensors into the battery manufacturing process is critical to achieving real-time, in-field monitoring without compromising cell performance or energy density. Embedding sensors directly into production lines (rather than retrofitting commercial cells in the lab) ensures mechanical compatibility and cost-effective scalability. Although demonstrations of fiber-optic and thin-film have provided rich internal insights, they depend on bulky equipment and ad hoc installation that can induce local stress, thermal hotspots, or unintended electrochemical disturbances. To bridge this gap, future work must co-design sensor fabrication and production workflows, embedding diagnostic hardware at optimal stages (for example, before electrolyte filling) to preserve electrode and separator integrity. Fig. 16 shows a future smart battery integrating multiple sensors. Concurrently, techniques

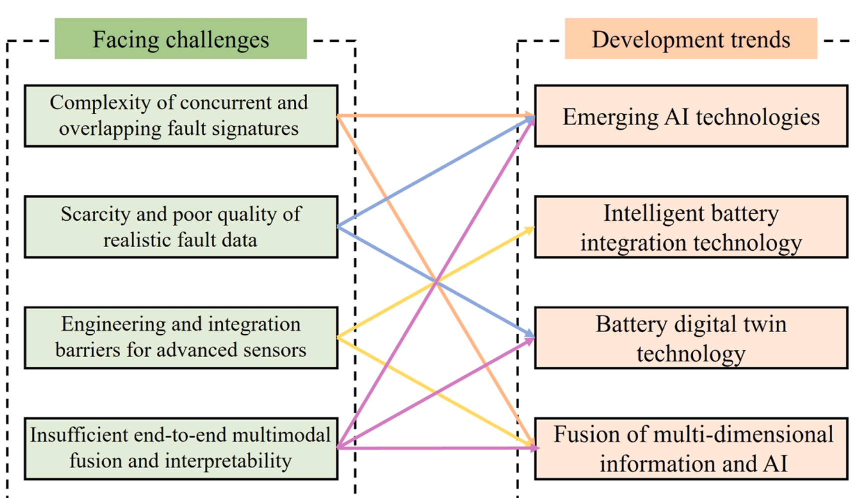

Fig. 14. The corresponding relationship between challenges and opportunities of integrating AI with advanced sensing technologies.

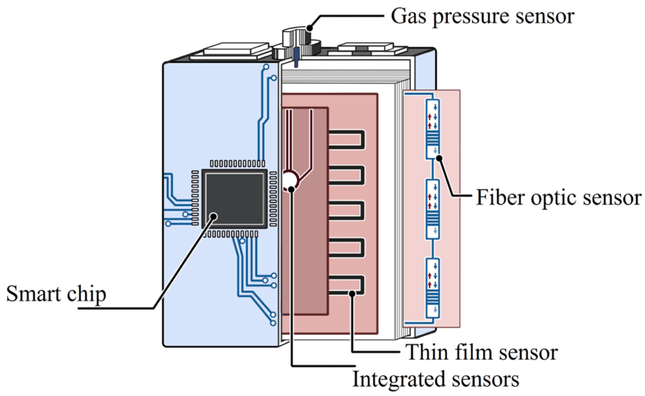

Fig. 16. Smart battery with integrated multiple sensors.

such as in situ EIS, ultrasound, and X-ray/CT should be miniaturized to meet the constraints of BMS. This can be achieved through dedicated analog front-ends for onboard spectroscopy modules or compact ultrasonic arrays, enabling the delivery of high-resolution data. Ultimately, the development of low-cost, self-calibrating sensor networks and standardized BMS interfaces will enable continuous, multi-dimensional fault diagnostics while maintaining battery integrity in commercial applications.

(3) High-fidelity battery digital twin technology offers a transformative platform for fault diagnosis by unifying internal and external multi-dimensional data streams within a continuously evolving virtual model. The framework of the battery digital twin is shown in Fig. 17. Initially, a comprehensive twin is constructed by integrating advanced sensing devices (such as in situ EIS, embedded temperature and pressure probes, and imaging modalities) to capture electrochemical, thermal, and mechanical parameters for accurate model parameterization and validation. During operation, the twin ingests real-time sensor feedback to dynamically update its state, enabling the simulation of fault initiation and propagation under actual loading and environmental conditions. This closed-loop interplay not only enhances the precision of AI-based diagnostic models (by supplying richly annotated, scenario-specific training data) but also permits rapid what-if analyses to predict emergent failure modes before they manifest physically. Moreover, digital twins can streamline failure testing by virtualizing destructive experiments, thereby reducing risk and accelerating the collection of fault data across diverse usage profiles. By providing both a physics-consistent simulator and a real-time data interface to AI algorithms, battery digital twin technology fundamentally elevates the robustness, interpretability, and scalability of next-generation fault diagnosis systems.

(4) Fault diagnosis algorithm based on multi-dimensional information fusion and AI technology. Fault diagnosis algorithms based on multi-dimensional information fusion and AI technologies are gaining increasing attention as traditional methods relying solely on voltage, current, and surface temperature signals struggle to accurately identify fault types. Integrating heterogeneous sensor data (such as electrode potential, internal temperature, pressure, acoustic, and imaging signals) offers a more comprehensive view of battery states. In this context, AI technologies, particularly multimodal neural networks, can effectively fuse these diverse data sources to enhance diagnostic accuracy. Notably, the emergence of large language models (LLMs) brings new opportunities for cross-modal representation learning and knowledge reasoning. By leveraging their powerful contextual understanding and generalization capabilities, LLMs can assist in interpreting complex sensor signals, guiding data labelling, and enhancing decision-making under limited supervision. Moreover, coupling multimodal DNN with battery physical models and LLM-based reasoning frameworks may enable more interpretable and mechanism-informed fault diagnosis, paving the way for intelligent, adaptive BMSs.

6. Conclusion

The rapid development of EVs and ESSs has heightened the need for efficient battery fault diagnosis technologies. The integration of AI with advanced sensors is crucial for enhancing fault detection and ensuring the safety, efficiency, and longevity of batteries. This review summarizes the latest progress in this area, outlining current research, challenges, and opportunities. Specifically, research in AI- and sensor-based battery fault diagnosis has made notable advances, yet several challenges remain: 1) Accurately identifying unknown faults or distinguishing between different fault types using limited operational data remains a significant challenge. 2) High-quality battery fault data required for AI training is difficult to acquire. 3) The practical implementation of advanced sensing technologies requires further optimization for real-world applications. 4) There is insufficient research on multimodal sensing information fusion and interpretability. Additionally, potential opportunities and future research directions are highlighted: 1) More advanced AI algorithms, such as explainable AI and PINN, can be developed and applied to enhance the accuracy and interpretability of battery fault diagnosis. 2) New smart battery manufacturing technologies should be explored to enable seamless integration of sensors during production while preserving energy density and safety. 3) Battery digital twin systems can be implemented to leverage multi-dimensional sensor data, enabling real-time monitoring and predictive maintenance. 4) Fault diagnosis algorithms based on multi-dimensional information fusion and advanced AI techniques can be designed to improve robustness across diverse operating conditions. These efforts are expected to provide valuable insights and inspire further investigations into this emerging and critical topic.

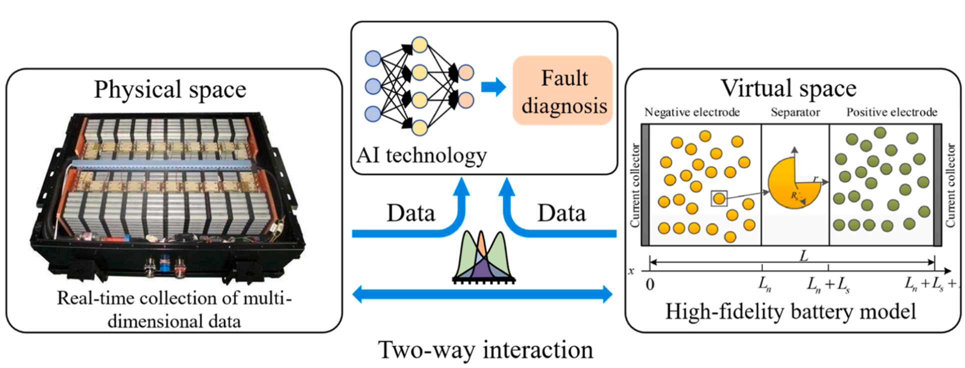

Fig. 17. The framework for battery digital twin technology for fault diagnosis.

CRediT authorship contribution statement

Kailong Liu: Supervision, Resources, Funding acquisition, Conceptualization. **Shiwen Zhao:** Writing – original draft, Validation, Methodology. **Yu Wang:** Writing – review & editing, Resources, Formal analysis. **Kang Li:** Writing – review & editing, Resources, Investigation. **Jiayue Wang:** Writing – original draft, Visualization. **Yaojie Sun:** Writing – review & editing, Software. **Qiuwei Wu:** Writing – review & editing. **Qiao Peng:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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