

Battery internal short circuit diagnosis based on vision transformer without real data

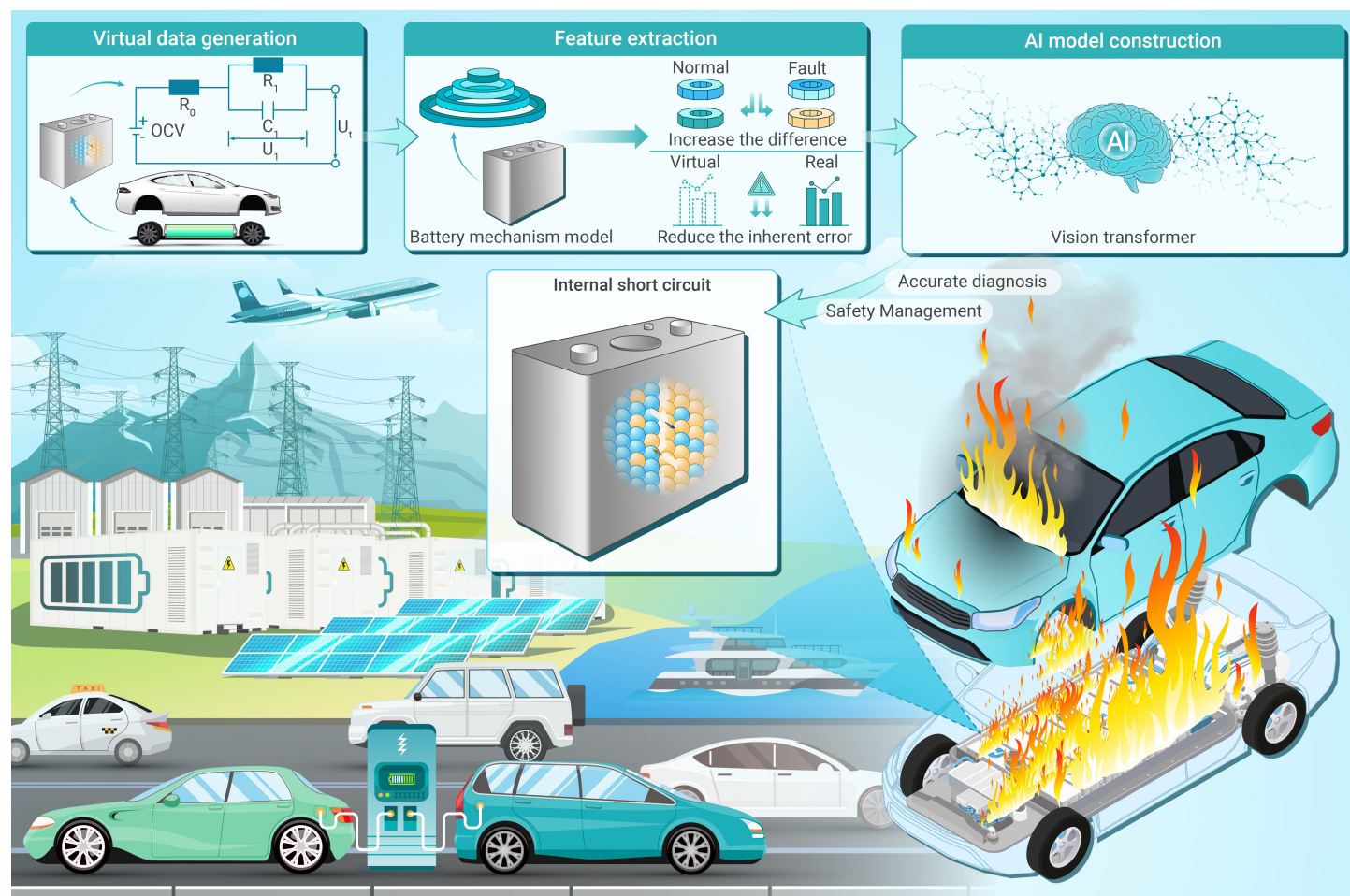
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Developing AI models for ISC diagnosis in lithium-ion batteries is challenging due to limited fault data.
- By extracting features from a mechanism model, AI model construction is achieved using only virtual data features.
- When applied to real ISC data, the model demonstrates high accuracy, robustness, and generalization.

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The diagnosis of an internal short circuit (ISC) fault is an integral part of thermal runaway warning for lithium-ion batteries. A higher level of accuracy in ISC fault diagnosis needs an artificial intelligence model, but lack of fault data and label ambiguity present challenges. To address these demands and challenges, features are extracted using a mean difference model to amplify the difference between fault data and normal data, while reduce the inherent error between virtual data and real data. Additionally, the model considers the influence of other faults and the variability within the real data. The Vision Transformer model is then trained with only this virtual feature to achieve 100% accuracy when verifying real ISC fault data under constant current charging condition. By breaking away from the reliance on real fault data for modeling, this approach greatly reduces the cost of human labor, materials, time, and carbon emissions, and also provides a reference for other projects facing similar challenges.

INTRODUCTION

The occurrence of thermal runaway in power batteries^{1,2} can result in significant property damage and potential personal injury, necessitating effective warning methods to minimize and prevent the losses and hazards associated with battery thermal runaway (TR). An internal short circuit (ISC) is a common cause of TR in batteries³ and is an essential indicator for assessing the risk of TR. The possible causes of ISC can be divided into two categories: production stage and usage stage.⁴⁻⁷ In the production stage, ISC may be caused by factors such as impurity particles, process defects, and electrode misalignment. In the usage stage, ISC is usually caused by mechanical abuse, electrical abuse,⁸ and thermal abuse.^{9,10} These causes result in a gradual progression of most ISC faults from minor to severe,¹¹ the severity of ISC is typically correlated with its equivalent resistance value. The lower the equivalent resistance value, the more severe the ISC severity.¹² Therefore, detecting ISC at higher resistance values implies a lower risk of TR and provides more sufficient risk mitigation time. Extensive research has been conducted by numerous scholars on effectively diagnosing ISC faults in batteries.¹³ These methods can be broadly categorized into two main types: data-driven approaches^{14,15} and model-based approaches.¹⁶ Data-driven methods employing remaining charge capacity¹⁷ or incremental capacity¹⁸ for quantitative diagnosis of ISC,¹⁹ however, these methods are contingent on specific operation conditions. Some researchers have also employed statistical methods²⁰ for effective identification of ISC faults, including correlation computation and entropy coefficients.²¹⁻²⁴ These methods primarily calculate abnormal information of faulty cells using statistical techniques but require empirical thresholds as diagnostic benchmarks. Model-based approaches typically employ equivalent circuit models²⁵ or electrochemical models²⁶⁻²⁸ for diagnosing ISC faults, this method can typically operate online, enabling early detection of ISC.²⁹ However, if the constructed models become excessively complex, an excessive number of unidentified parameters will hinder its application on real scenarios. With the rapid advancement of artificial intelligence (AI) algorithms,³⁰ the research on utilizing AI models for battery management systems has shown an explosive growth trend.³¹ This trend is not only driven by the rapid advancement of AI algorithms but also supported by the availability of massive cloud-based data,³²⁻³⁴ as well as the urgent need to efficiently apply AI models to large databases. It underscores the necessity of utilizing AI models for ISC diagnosis in future cloud-based battery safety management.³⁵ However, within the vastness of cloud data,³⁶ fault

data is extremely scarce.³⁷ Furthermore, obtaining labels for fault data is challenging due to the complex electrochemical mechanisms of batteries. Therefore, the lack of effective fault data poses an obstacle to the construction of AI models.

In this context, many scholars have obtained training data through experiments to achieve data augmentation, so that AI models can accurately diagnose ISC from qualitative³⁸⁻⁴⁰ or quantitative^{41,42} perspectives. However, the need for a large amount of training data inevitably incurs high costs, as well as the inherent risks associated with conducting extensive experiments. Another approach for data augmentation is to generate a sufficient amount of virtual data through simulation models. However, this method still relies on real data and requires transfer learning to bridge the gap between virtual and real data, in order to improve the accuracy of the model.^{43,44} Although this approach reduces the reliance on real data, it is still constrained by the method in which real data is obtained, making it challenging to flexibly construct the model and limiting its applicability for expansion. Therefore, breaking free from the reliance on real data and training AI models solely using virtual data for ISC diagnosis is undoubtedly a low-cost and highly flexible solution. As depicted in Figure 1, the Thevenin model is utilized as the foundation to construct a module-level fault simulation model. Ample virtual data on ISC of varying degrees of severities, as well as data for two types of interference faults, low state of charge (SOC) and low capacity, are generated to enhance the robustness of the model. The voltage Mean Difference Model (MDM) is employed for feature extraction, significantly enhancing the distinction between faulty and normal data, and reducing the inherent discrepancies between virtual and real data. Concurrently, to enhance the model's generalizability, we amalgamate feature values from multiple starting voltage positions to construct the training dataset. Construct a Vision Transformer (ViT) model and adjust the hyperparameters to adapt to the training dataset. Design fault experiments, validating the model's diagnostic accuracy with real data, aiming for an accuracy rate of 100%. The result demonstrates that the integration of virtual data with the MDM effectively eliminates the dependence of model construction on real data. The proposed framework undoubtedly significantly reduces the cost and potential risks associated with obtaining real data, enhancing the flexibility of model construction. Accurate fault diagnosis enhances the operational safety of battery systems, promoting their widespread application and development in scenarios such as electric vehicles, electric ships, electric aircraft, and energy storage systems. This also provides a reference for other work facing similar challenges. The main contributions of this research are summarized as follows:

(1) A ViT model is constructed solely based on virtual ISC data, achieving a diagnosis of real ISC data with an accuracy rate of 100%.

(2) By utilizing the MDM for feature extraction, the difference between normal and fault data is significantly increased, effectively reducing the inherent error between virtual and real data.

(3) Considering actual working conditions, two types of interference faults are incorporated to verify the robustness of the model. Data diversity from multiple starting voltage points is combined to validate the generalizability of the model.

MATERIALS AND METHODS

Data augmentation

As shown in Figure 1A, a cell simulation model is constructed based on a Thevenin model, as represented in Equation 1. Model parameters are identi-

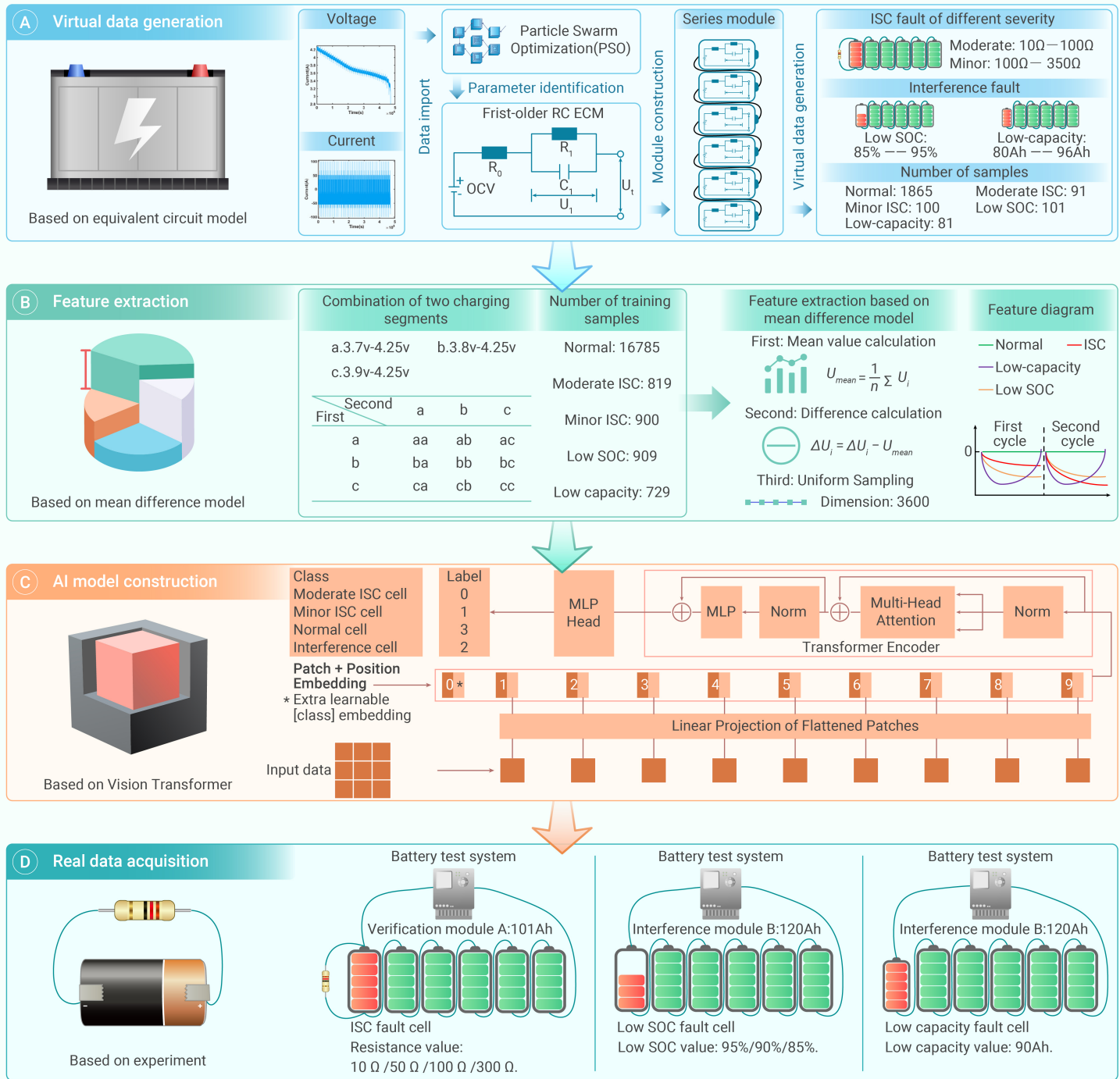


Figure 1. The process of building AI models based on virtual data.

fied through a combination of actual test data and the Particle Swarm Optimization algorithm, the values for the Ohmic resistance R_0 , polarization resistance R_1 , and time constant τ_1 are obtained. By connecting cells in series, a battery module containing six cells is constructed.

$$\begin{cases} U_t = OCV - I \times R_0 - U_1 \\ U_1 = I \times R_1 [1 - \exp(-t/\tau_1)] \end{cases} \quad (1)$$

Where U_t represents the terminal voltage, OCV represents the open circuit voltage, I represents current, U_1 represents polarization voltage, t represents time, τ_1 represents time constant.

Three types of faults are considered: low SOC, low capacity, and ISC of varying severity. The fundamental impact of ISC faults on the battery is the leakage current, which can be represented by an equivalent short circuit (SC) resistance. This resistance directly describes the severity of the ISC. SC

resistances below 10Ω lead to a significant decline in the voltage curve, which is a distinct characteristic that does not require diagnosis. Conversely, SC resistances exceeding 350 Ω have a negligible effect on the battery and are classified as normal. For ISC fault, the total current I is composed of two components, leakage current I_{leak} and normal current I_{normal} , as shown in Equation 2. The charging current is defined as positive, and the discharging current as negative, therefore I_{leak} is always negative. The leakage current is obtained by dividing the terminal voltage U_t , generated by the equivalent circuit model, by the set SC resistance R_{ISC} , as shown in Equation 3. In the simulation model, the SC current and the normal current can be considered as known variables. However, in actual operating conditions, only the normal current can be measured, while the SC current cannot be directly measured.

$$I = I_{normal} + I_{leak} \quad (2)$$

$$I_{\text{leak}} = \frac{U_i}{R_{\text{ISC}}} \quad (3)$$

For low SOC faults, the SOC of the faulty cell is set lower than that of other normal cells. For low-capacity faults, the capacity value of the faulty cell is set lower than that of other normal cells.

Feature extraction

The inevitable discrepancy between virtual and real data presents substantial challenges when deploying models trained on virtual data to real-world scenarios. Conventionally, this obstacle is surmounted by conducting transfer learning on real data. To achieve independence from real data solely using AI models is unattainable, it is essential to effectively integrate battery mechanism models into the construction of AI models. Therefore, feature extraction is conducted by using the MDM, the expression of which is presented in Equation 4. Since U_{mean} is inclined to reflect the measurements of normal cells, and anomalous cells are characterized by deviations from these normal values, the features of anomalous cells can be amplified through ΔU_i . As illustrated in Figure 1B, the schematic of the results distinctly segregates normal data from fault data, and a clear distinction is also present between ISC faults and interference faults.

$$\begin{cases} U_{\text{mean}}^t = \frac{1}{n} \sum_{i=1}^n U_{i,t} \\ \Delta U_{i,t} = U_{i,t} - U_{\text{mean}}^t \end{cases} \quad (4)$$

Where U_{mean} represents the mean voltage, and n represents the number of cells in the module. U_i denotes the voltage of the i^{th} cell, ΔU_i represents the difference between the voltage of the i^{th} cell and the mean voltage, t represents the sample number.

VIT model construction

The Transformer,⁴⁵⁻⁴⁷ known for its powerful capability in handling sequential data, is widely used in the field of natural language processing. The ViT model segments an image into a series of small patches and treats these patches as sequential data, which are then processed by the Transformer. This model, which can handle both image data and leverage the Transformer's sequential processing capability, is highly suitable for identifying voltage-related features. The ViT model incorporates a global self-attention mechanism, leveraging global information for image processing. In conjunction with a multi-head attention mechanism, it facilitates the establishment of associations between different image positions. This mechanism proves particularly adept at processing voltage time-series data. It can effectively construct correlations between the features of each cycle, discern the trend of feature alterations across different cycles, and thereby accurately gauge the severity of ISC. The structure of the model is shown in Figure 1C, and the process of data flow is described in conjunction with Table 1. In step 1, the shape of the input data X is $H \times W \times C$, where (H, W) represents the resolution of the original image and C represents the number of channels. Furthermore, the image is transformed into a flattened two-dimensional block sequence X_p , which consists of N flattened two dimensional blocks with dimensions $(P^2 \times C)$, (P, P) is the resolution of each image patch. In step 2, to obtain an input matrix of size (N, D) , patch embedding is performed on X_p , where each vector undergoes a linear transformation to compress the dimensions of the flattened two-dimensional block sequence to D . Z_0 is the input sequence, where E represents a fully connected layer with an input channel of $(P^2 \times C)$ and an output channel of N . X_{class} is an additional learnable class embedding. E_{pos} serves as a position encoding to supplement the positional information of the sequence, while also incorporating a learnable positional embedding. In step 3, the Transformer encoder is composed of alternating layers of multi-head self-attention (MSA) and multi-layer perceptron (MLP) blocks, with a total of L layers. Layer normalization (LN) is applied before each block, and residual connections are applied after each block. Z'_l and Z_l correspond to the processed results at each block. The final image representation output, denoted as y , is obtained from the Transformer encoder (Z_L^0) at the state of output.

Given that the feature data is a one-dimensional vector, retaining its original shape in the newly constructed image would result in substantial blank

Table 1. The data calculation process of ViT model

Step1. Data input sub-model

$$\begin{aligned} X &\in \mathbb{R}^{H \times W \times C} \\ X_p &\in \mathbb{R}^{N \times (P^2 \cdot C)}, N = H \times W \div P^2 \end{aligned}$$

Step2. Patch embedding and positional embedding

$$\begin{aligned} Z_0 &= [X_{\text{class}}; X_p E; X_p^2 E; \dots; X_p^N E] + E_{\text{pos}} \\ E &\in \mathbb{R}^{(P^2 \cdot C) \times D}, E_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \end{aligned}$$

Step3. Transformer encoder and output

$$\begin{aligned} Z'_l &= \text{MSA}(\text{LN}(Z_{l-1})) + Z_{l-1}, l = 1 \dots L \\ Z_l &= \text{MLP}(\text{LN}(Z'_l)) + Z'_l, l = 1 \dots L \\ y &= \text{LN}(Z_L^0) \end{aligned}$$

Table 2. The hyperparameters of the ViT

Patch size	Dim	Depth	Heads	Mlp_dim	Dropout	Emb_dropout
60	20	10	4	64	0.1	0.1

areas, making it challenging for the model to capture the characteristics of the curve. To reshape the data, the new form will be a (60×60) grayscale image. During the reconstruction, a (60×60) empty matrix is created first, and then the feature values of the one-dimensional vector are filled in sequentially, ensuring that the original sequence is preserved. The relevant hyperparameters of the model are presented in Table 2. The Patch size refers to the number of small blocks into which the model divides the image, each patch is treated as an independent input sequence. The Dim represents the dimension of the vector space used by the model for internal information processing. The Depth indicates the number of layers in the Transformer encoder, each containing a self-attention mechanism and a feedforward neural network. The Mlp_dim is the size of the hidden layer in the feedforward neural network of the Transformer encoder. Dropout is the proportion of neurons randomly dropped to prevent overfitting, and Emb_dropout is the proportion of the embedding layer randomly dropped for the same purpose. For the model training process that involves only virtual data input without real data, the final output consists of category numbers: 0 for moderate ISC fault cells, 1 for minor ISC fault cells, 2 for interference fault cells, and 3 for normal cells.

The model's optimizer is set to Adam with an initial learning rate of 10e-5. Adam will adaptively optimize the learning rate during training. Additionally, L2 regularization is set to prevent the model from overfitting on the training dataset, with the parameter set to 0.01. The model is trained for 3000 epochs, with a training dataset size of 20142×3600, and the total training time is 6023 seconds (1 hour 40 minute). This model is used for offline diagnosis, and the time required to diagnose the current validation set (432×3600) is 1.19 seconds. The model development is based on the PyTorch machine learning library in Python, and the computation is executed on an NVIDIA GeForce RTX 4090 graphics processing unit (GPU). The accuracy and loss values during the model training process can be found in the supplementary text section of the Supplementary Information.

RESULTS

Virtual data generation

To address the challenges of the scarcity of ISC fault data and label ambiguity, we first generated a substantial amount of virtual data based on module-level simulation models, as shown in Figure 1A. This data encompasses ISC faults of moderate and minor severity, two types of interference (low SOC and low-capacity), as well as normal data. For moderate ISC, the resistance values range from 10 to 100 Ω , totaling 91 data sets. For minor ISC, the resistance values span 101 to 350 Ω , with a total of 100 data sets. A low SOC fault occurs when one cell within the module has a lower SOC compared to the other cells. Similarly, a low-capacity fault arises when one cell within the module exhibits abnormal capacity degradation. The voltage

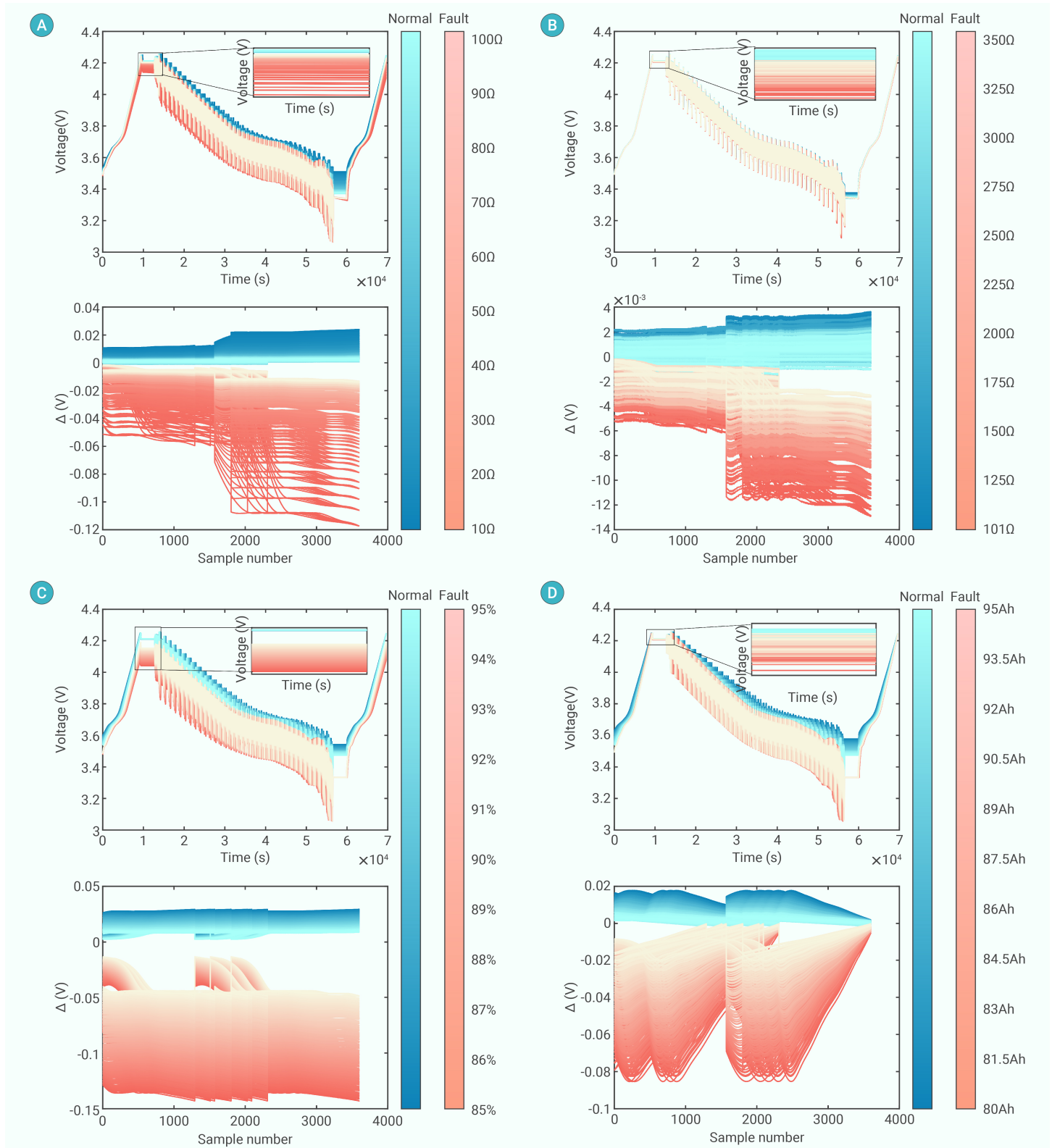


Figure 2. Virtual data and feature data curve (A) The curve of the moderate ISC faults. (B) The curve of the minor ISC faults. (C) The curve of the low SOC faults. (D) The curve of the low-capacity faults.

characteristic associated with these two faults exhibit a high degree of similarity to ISC faults, rendering them prone to causing false positive detections. Consequently, to enhance the robustness of model, these two faults are incorporated as interference faults in the virtual data. For low SOC faults, the range is set between 85% and 95%, while the SOC of the normal cells is 100%, comprising a total of 101 data sets. For low-capacity faults, the range is set

between 80 and 96 Ah, while the capacity of the normal cells is 101 Ah, resulting in 81 data sets. In total, there are 1865 data sets for normal conditions. All simulations undergo two charge-discharge cycles, with cell 1 designated as the faulty cell.

The charging conditions eliminate the high stochasticity in discharge process, providing a more stable and reliable dataset. However, in practical

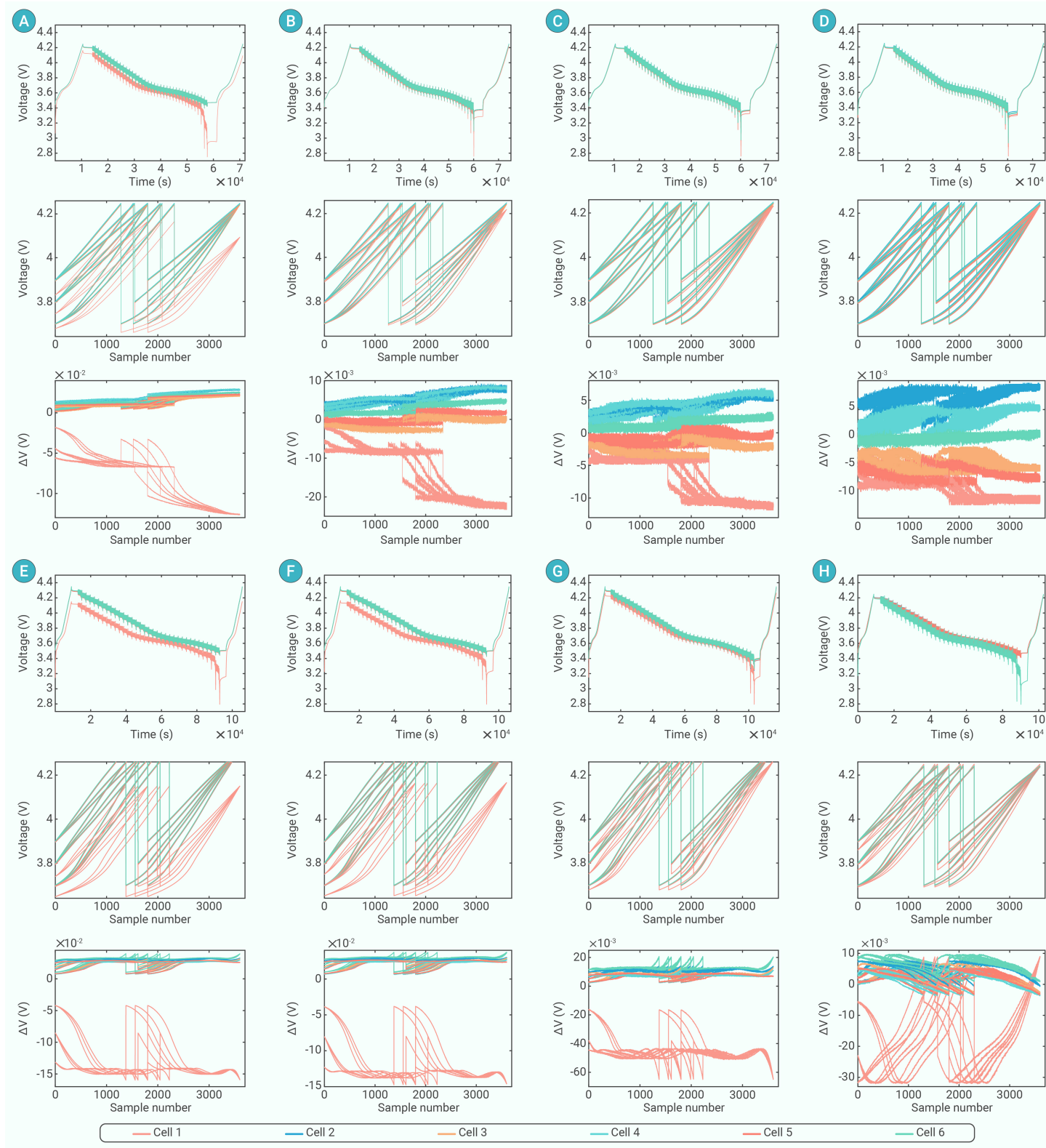


Figure 3. The experimental test voltage curve, the original curve of the two-cycle charging voltage combination, and the feature curve of the two-cycle charging voltage combination extracted by MDM (A) ISC 10Ω. (B) ISC 50Ω. (C) ISC 100Ω. (D) ISC 300Ω. (E) Low SOC 85%. (F) Low SOC 90%. (G) Low SOC 95%. (H) Low-capacity. In each subplot, from top to bottom, the following are presented sequentially: experimental test voltage curve, combination of original voltage curves for two-cycles, and combination of feature curves for two-cycles extracted by MDM.

charging scenarios, fully charge is relatively rare. Therefore, it is necessary to account for the randomness of the initial charging voltage to enhance generalization capability of model. As illustrated in Figure 1B, we select three starting voltage points: 3.7 V, 3.8 V, and 3.9 V, corresponding to SOC of 42%, 57%, and 67%, respectively. These high-frequency voltage points are readily avail-

able in actual charging process, it does not imply that the starting charging voltage must be exactly 3.7V, 3.8V, or 3.9V. This means that when the starting charging voltage is below 3.9V, suitable starting voltage data can be used as model input. This approach significantly increases the range of usable data, thereby enhancing the model's generalization capability. Simultane-

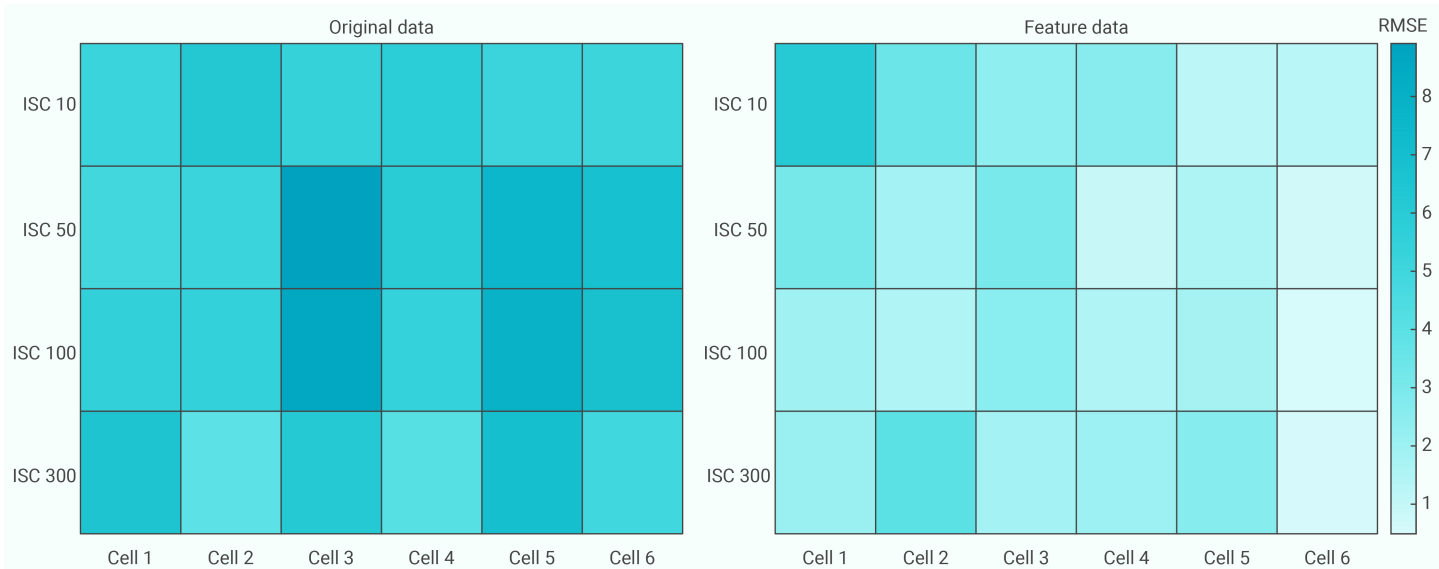


Figure 4. Comparison of the mean RMSE between virtual data and real data before and after feature extraction.

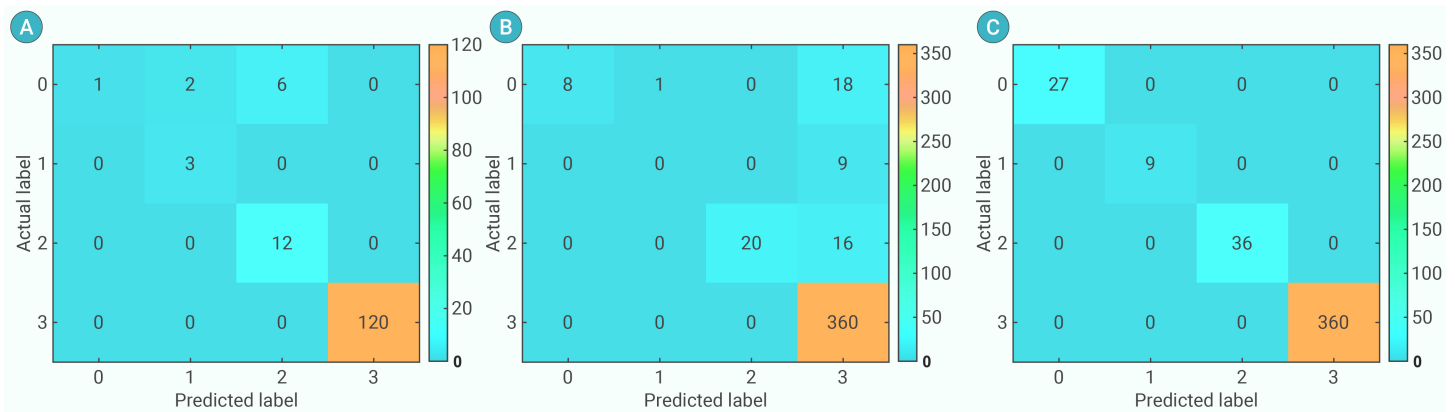


Figure 5. The diagnosis results of the ViT model (A) Data extracted features through MDM in the one-cycle. (B) Data not extracted features through MDM in the two-cycle. (C) Data extracted features through MDM in the two-cycle.

ously, low SOC faults and ISC faults exhibit an extremely high degree of similarity within one cycle, and relying solely on the features from one cycle would misdiagnose interference faults as ISC. Consequently, at least two charging cycles are required to effectively discriminate between ISC faults and interference faults. Both of these charging features incorporate randomness in the initial charging position, resulting in nine possible combinations. In total, there are 16,785 normal samples, 819 moderate ISC samples, 900 minor ISC samples, 909 low SOC samples, and 729 low-capacity samples. Furthermore, we employ the MDM for feature extraction and uniformly resample all training samples to a dimension of 3,600 through uniform sampling.

The virtual data presented in Figure 2 shows the original voltage curves at the top and the feature curves processed by MDM at the bottom of each subplot. Figure 2A and 2B represent the voltage and feature curves for moderate and minor ISC faults, respectively. While the voltage curves of all samples are displayed, they overlap significantly, making it visually challenging to discern the pattern of voltage curves as resistance changes. However, the feature graphs clearly demonstrate that as the resistance increases, the feature curves of the faulty cells gradually approach those of the normal cells. This aligns with the corresponding pattern between resistance magnitude and short-circuit (SC) current: the larger the resistance, the smaller the SC current. Consequently, within the same cycle, the leakage current of the SC cell is less, resulting in a smaller voltage drop, and the difference between the features of the faulty and normal cells diminishes, and vice versa. It can be distinctly observed that the feature values in the second cycle are lower than those in the first. This is due to the continuous presence of SC current and

the constraints imposed by the upper and lower voltage cut-off on the module, which progressively reduce the amount of charge that can be accommodated by the faulty cell. Figure 2C presents the voltage curves for low SOC faults alongside the feature curves, where the feature data from the faulty cell is distinctly separated from that of the normal cell. Low SOC faults, as a form of steady-state module inconsistency, exhibit the same characteristics across different cycles, in contrast to ISC faults, which progressively deviate from normal feature with increasing cycle numbers. This distinction enables the model to effectively differentiate between low SOC faults and ISC faults. Figure 2D presents the voltage and feature curves of the low-capacity fault, where the feature curves clearly separate the faulty data from the normal data, which overlap in the original voltage curves. Within the same cycle, the features of low-capacity faults can be divided into two stages: the initial to mid stage shows a drop in feature values, deviating and resembling the characteristics of ISC faults, while in the latter stage, the values gradually approach normal, exhibiting a decline followed by an increase.

Experiment data generation

Experiments are designed to involve ISC faults of varying severities, low SOC, and low-capacity to obtain real data. Detailed information about the experiments is provided in the supplementary text section of the Supplementary Information. The experimental results are depicted in Figure 3. The starting voltages in the combination graph are 3.7V, 3.8V, and 3.9V, respectively, consistent with the features of the training set. Figure 3A-D represent the results of the ISC module with resistance values of 10Ω, 50Ω, 100Ω, and

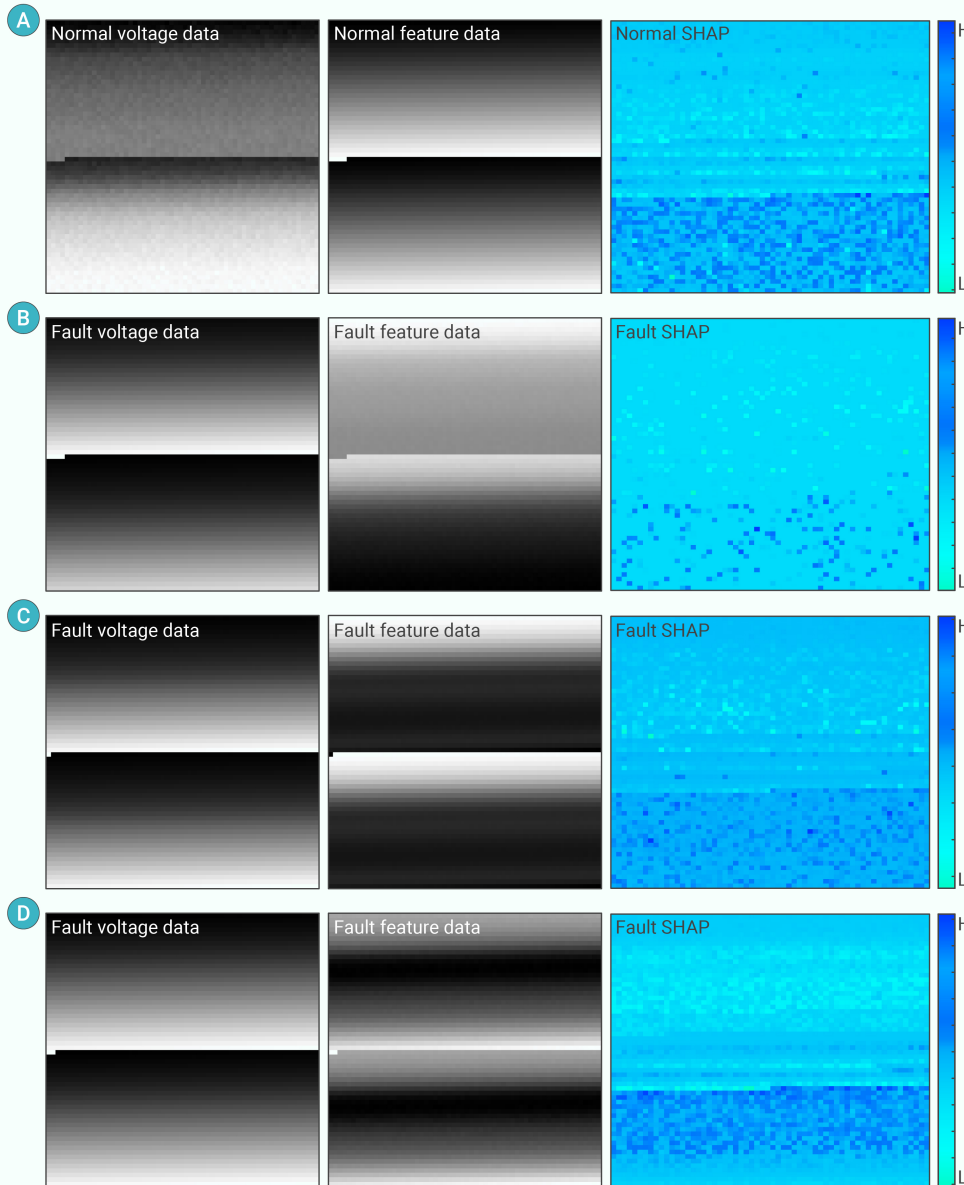


Figure 6. Grayscale images and SHAP (SHapley Additive exPlanations) graphs of different types of fault data (A) Normal cell. (B) ISC 10Ω. (C) Low SOC85%. (D) Low-capacity. In each subplot, from left to right, the following are presented sequentially: the grayscale image of the combined original voltage curves for two-cycles, the grayscale image of the combined feature curves for two-cycles, and the SHAP graph of the combined feature curves for two-cycles.

The advantages of the MDM feature extraction are qualitatively analyzed, and the Root Mean Square Error (RMSE) differences between the virtual data and experimental data for ISC faults are further calculated before and after feature extraction. The calculation of RMSE is given by Equation 5. The RMSE for low SOC faults and low-capacity faults is not calculated because the experimental data for these faults is obtained from Module B, whereas the simulation data is generated based on the parameters of Module A, rendering the calculation meaningless. Detailed content of Module A and B are provided in the Supplementary Information.

$$RMSE_j = \sqrt{\sum_{i=1}^n \frac{(D_{vi}^j - D_{ri}^j)^2}{n}} \quad (5)$$

Where $RMSE_j$ represents the RMSE of the j^{th} cell in the same module, D_{vi}^j represents the virtual value of the j^{th} cell at time i , D_{ri}^j represents the real value of the j^{th} cell at time i , n represents the sample dimension.

As illustrated in Figure 4, the RMSE after feature extraction is significantly lower than that of the original voltage. This improvement is attributed to the MDM process, where the voltage value of each cell is differenced from the mean voltage value. This involves subtracting the error by the mean error, which notably reduces the RMSE between the virtual data and the real data, thereby making the

virtual features more analogous to the real features. This supports the notion that a model trained solely on virtual data can effectively diagnose real data. Additionally, the subtraction process is equivalent to normalizing the data.

300Ω, respectively. As the SC resistance value increases, the experimental data and virtual data exhibit the same trend: the faulty cell voltage gradually approaches the normal cell voltage, and the feature value changes accordingly. In the experimental test voltage curve and the combined original curve, there is a clear distinction between the 10Ω faulty cell and the normal cell, while the 50Ω and 100Ω fault data gradually overlap with the normal data, and the 300Ω fault data is almost indistinguishable from the normal cell. However, in the feature curve, even with 300Ω, the fault features are clearly distinguishable from the normal features. After feature extraction with MDM, there is a significant difference between the faulty and normal features, making MDM feature extraction beneficial for the model to effectively diagnose ISC of varying severities. Figure 3E-G represent the results of the low SOC fault module at 85%, 90%, and 95%, respectively. Compared to the one-cycle charging curve segment, the low SOC fault is very similar to the ISC fault. Figure 3H represents the low-capacity fault, where the curve of the faulty cell in the one-cycle charging curve from the beginning to the middle section also shows similarity to the ISC fault. The analysis of different fault experimental data and features indicates that both low SOC and low-capacity faults can interfere with the diagnosis of ISC faults. Relying solely on one-cycle charging data cannot effectively distinguish them, and the actual demand for different starting voltages further increases the difficulty of differentiation. Therefore, it is necessary to capture the differences between ISC faults and interference faults through two-cycle charging data.

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Results of model classification

Figure 5 presents the diagnostic results obtained from different data processing methods. In Figure 5A, which includes only one-cycle charging data processed through MDM feature extraction, the results indicate that the model can accurately distinguish between fault and normal data but cannot effectively differentiate between ISC faults and interference faults. One-cycle data do not require combinations, resulting in a smaller number of validation samples compared to two-cycle data. Figure 5B shows the results for two-cycle charging data without MDM feature extraction, where the model fails to accurately separate fault data from normal data, yet it does not confuse ISC faults with interference faults. Figure 5C, involving two-cycle charging data processed with MDM feature extraction, clearly distinguishing between fault and normal data, as well as between ISC faults and interference faults, demonstrating remarkable robustness and generalizability. Additionally, data containing noise is also validated, and the results show that even with the addition of noise with an amplitude of 10mV and conforming to a Gaussian distribution, the accuracy of the diagnosis still reaches 99.3%, proving that the model has good robustness against noise. Specific details can be found in the supplementary text section of the Supplementary Information.

To further analyze the interpretability of the model's diagnostic results, Figure 6 presents grayscale images of normal and fault data from three different experiment, along with the corresponding Shapley Additive exPlanations (SHAP) graphs. Figure 6A for shows the results for a normal cell, Figure 6B for an ISC with a 10 Ω resistance, Figure 6C for a low SOC of 85%, and Figure 6D for the low capacity. The grayscale images visualize the data shape after reconstruction, while SHAP, a method based on cooperative game theory, calculates the marginal contribution of features to the model output and provides a visualization of this process. Comparing the grayscale images of normal and fault data in the original voltage, the arrangement of the graphs is very similar, and there is also a high degree of similarity between different faults. However, for the grayscale images of normal and fault data in the feature, there are significant differences. When comparing the fault grayscale images of the three faults, clear distinctions are also observed. Analysis of the grayscale images before and after feature extraction using MDM proves that MDM can effectively enhance the differences between input data with different labels. Analyzing all the SHAP graphs reveals that the latter half of the grayscale images contributes most to the diagnostic results, corresponding to data from the second charging cycle. This also demonstrates that data from two cycles is essential for the model's accurate diagnosis. In summary, after applying the MDM feature extraction to the two-cycles charging data, the model trained solely on virtual data accurately diagnosed real ISC faults of varying severities. Additionally, the model's generalizability to different starting voltages and robustness against interference faults are validated. Using a subset of data from a 10 Ω fault as an example, we describe in detail the process from original data to the final diagnostic result through mathematical expressions and pseudocode. This content can be found in the supplementary text section of the Supplementary Information.

DISCUSSION

The analysis of the results section demonstrates the effectiveness of the proposed method on the dataset used in the paper, enabling the construction of AI models for lithium-ion battery ISC fault diagnosis to be independent of real data. However, challenges remain when applying this method to actual working conditions, necessitating further advancements and exploration in the future. The parameters of the battery model established in the paper have not yet considered the effects of battery aging and temperature. Therefore, a real-time parameter identification scheme needs to be established so that model parameters can be accurately updated to track the battery's aging state. Given that the battery thermal management system can ensure charging within a safe temperature range, charging data can be screened based on a reasonable temperature range to enhance diagnostic reliability. Additionally, the application of multi-stage fast charging is also a factor that needs to be considered. Since the fault simulation model in the paper is based on the essential characteristics of ISC faults and the abnormal leakage of the battery cell, making it theoretically possible to generate usable virtual data even if the charging conditions are changed, this still requires practical verification in future applications. For cloud-based big data applications, the model presented in the paper is an offline diagnosis. Given the randomness of charging data, we set the feature segments to be obtained at different starting voltage positions to enhance the generalization of the model and the convenience of feature extraction. The coverage range of the features is from the mid to high SOC range. In the future, to further improve the diagnostic speed of the model, we should divide the feature segments into smaller SOC ranges, minimizing the time required to obtain the feature segments and expanding the coverage of the feature segments. This will enhance the convenience and timeliness of feature extraction.

In the trend of intelligent development of cloud battery management system, the effective application of AI models will become the core of transformation. The method proposed in this paper not only enhances the flexibility of building AI models, but also significantly reduces the cost of constructing datasets while ensuring the effectiveness of model applications. This approach can be applied to battery safety management in various scenarios such as electric vehicles, electric ships, electric aircraft, and energy storage systems. In future work, overcoming the aforementioned challenges and applying this method to real-world ISC diagnosis will be our direction for further advancement.

CONCLUSION

In the context of rapidly growing cloud data, accurately diagnosing ISC faults using AI models presents challenges due to the lack of fault data and vague labels. In response to these challenges, we have successfully achieved 100% diagnostic accuracy with a ViT model trained solely on virtual data while validated on real data. Our work consists of two main parts:

(1) A simulation model is built at the module level to generate virtual training data. The virtual data includes ISC fault data of varying severities, low SOC, low-capacity, and normal cell. Considering the randomness in real charging conditions, three high-frequency charging voltage positions (3.7V, 3.8V, 3.9V) are selected and combine the data from two charging cycles to verify the generalizability of the model.

(2) The MDM is further utilized for feature extraction, which significantly enhances the difference between normal and faulty features and reduced the inherent error between virtual and real data. A ViT diagnostic model is trained by the virtual feature data. Fault experiments are also designed to obtain real data to validate the diagnostic accuracy of the ViT model. The experimental modules for low SOC and low-capacity do not correspond to the simulation model, which undoubtedly enhances the interference ability. The results show that even with the interference faults and the diversity of multiple charging starting position combinations, the model still achieves 100% diagnostic accuracy.

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AUTHOR CONTRIBUTIONS

Y.Z. and conceived the idea, led and supervised the project, participated in paper writing and revision, and provided guidance to all co-authors. M.O. supervised and led this project. H.C. generated the data, conceived, wrote, and revised the manuscript. X.L., L.S., Y.X., Y.W., X.H. and Y.S. were involved in the writing, review, and editing of this manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Data and code are available from the corresponding authors upon request.

SUPPLEMENTAL INFORMATION

It can be found online at <https://doi.org/10.59717/j.xinn-energy.2024.100041>

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