State of Health Estimation of Lithium-ion Batteries Based on LLM-BiLSTM Model

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Abstract. This study proposes a state of health (SOH) estimation method for the lithium-ion batteries based on a Large Language Model (LLM) and BiLSTM model, aiming to capture the complex dynamic characteristics during the performance degradation process of lithium batteries through deep learning models. First, the charge-discharge data of lithium batteries is pr-processed, including data cleaning and normalization, to ensure the effectiveness of model inputs. Next, cross-attention is employed to reconstruct the charge-discharge data into text format, aligning data modalities with text modalities. Text prompts for this task are then input into the LLM model, with tokenization and encoding performed to obtain input encodings. Subsequently, these input encodings and the cross-attention reconstructed features are jointly fed into the LLM model for feature extraction. Finally, the features extracted by the LLM model, along with the charge-discharge data of the lithium batteries, are input into the BiLSTM model for SOH prediction. To validate the model's effectiveness, various experiments were conducted using a historical dataset of cyclic aging from commercial 21700 lithium-ion batteries (LG M50T).

Keywords: State of Health (SOH), Lithium-ion battery, Large Language Model, Attention Mechanism

1 Introduction

With the intensification of global climate change and environmental pollution issues, the sustainable development of the environment and resources has become a central theme in the efforts of countries worldwide to achieve carbon neutrality and carbon emission policies. In September 2020, China committed to achieving peak carbon emissions by 2030 and carbon neutrality by 2060[1], This ambitious target will further drive the development and utilization of renewable energy. Lithium batteries, as an efficient energy storage device, possess advantages such as compact size, long cycle life, low self-discharge rate, and environmental friendliness[2], and have been widely applied in electric vehicles and renewable energy storage. However, under the influence of prolonged cycling, high temperatures, and other factors, the capacity of lithium batteries tends to decline, leading to aging. Battery aging can result in performance degradation, and if the batteries are not replaced in time before reaching the failure threshold, unexpected incidents such as overheating, short circuits, or even fires and explosions may occur. This can cause system malfunctions, prevent normal operation, and pose serious safety hazards[3]. Therefore, effective monitoring and management of lithium battery lifespan are crucial for ensuring battery safety, significantly impacting the safety and operational efficiency of electric vehicles and energy storage systems.

The State of Health (SOH) is one of the critical metrics for determining the lifespan of lithium batteries, with estimation methods mainly divided into two categories: model-based methods and data-driven methods[4]. However, equivalent circuit models cannot capture all the physical and chemical processes within the battery, limiting their accuracy under different conditions and failing to accurately describe the highly nonlinear behavior exhibited by lithium batteries. Electrochemical models, while based on the internal physical and chemical processes of the battery, typically involve complex partial differential equations, requiring substantial computational resources and time to solve, thus presenting a very high computational complexity.

Compared to the aforementioned methods, deep learning, as a data-driven approach, can discover the complex nonlinear relationships within lithium batteries by learning from extensive historical data and training multilayer neural networks for high-level nonlinear fitting[5]. A novel prediction method that combines the attention mechanism (AM) is introduced in [6], building on the LSTM approach. By applying a moving average filter to reduce noise and using AM to enhance the weight allocation of important information in the LSTM hidden layer for battery capacity data under different datasets and discharge rates, the accuracy of SOH prediction is significantly improved. An improved Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model that effectively captures multi-scale features and overcomes the gradient vanishing problem in LSTM models is proposed in [7]. This is achieved by introducing feature selection and skip connection mechanisms, thereby significantly enhancing the estimation accuracy of lithium battery SOH. However, from the above studies, it is evident that past research methods have primarily relied on unimodal historical data, without considering multimodal data fusion for SOH prediction. Leveraging the complementary nature of different modalities can enhance the accuracy of SOH prediction. Strategies for time-series prediction using Large Language Models (LLMs) are explored in [8], effectively addressing the modal alignment issue between time-series data and natural language. However, this approach has limitations: it uses only a single past feature value to predict the future value of that feature, without considering the influence of other related features. Moreover, the model's predictions rely solely on text features extracted by the large model, considering only the text modality and not combining historical data with textual information, which may affect the comprehensiveness and accuracy of the predictions. To address these issues, this paper proposes a LLM-BiLSTM model based on multimodal fusion, which improves the SOH prediction accuracy of lithium batteries by aligning text and discharge data with multimodal features and processing the aligned multimodal data using the LLM model.

2 Proposed Method

2.1 LLM-BiLSTM Model Structure

The charge-discharge process of lithium-ion batteries is highly complex, and the data features obtained from charge-discharge experiments are insufficient to fully characterize this process[9].To address the above issue, this paper proposes an LLM-BiLSTM-based SOH prediction model for lithium batteries. This approach comprehensively considers both text and data features, leveraging their complementary information, and incorporates task-specific textual prompts into the LLM, thereby enhancing prediction accuracy. The structure of the LLM-BiLSTM model is illustrated in Figure 1.

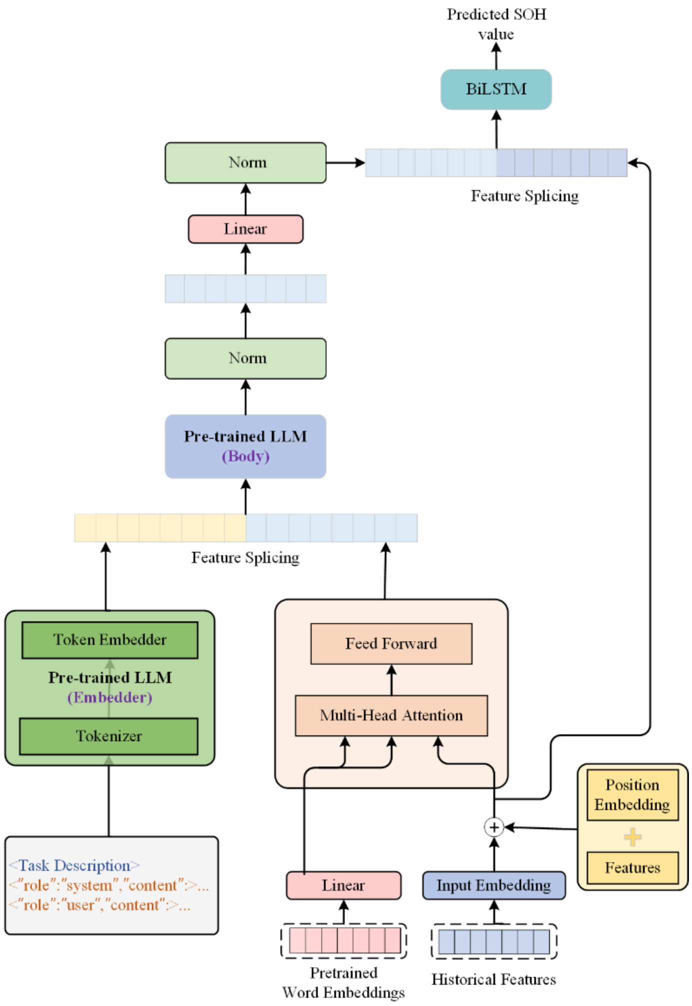

Fig. 1.LLM-BiLSTM MODEL Structure

The LLM-BiLSTM model is primarily composed of four parts: the Embedder Module of the Pre-trained LLM, the Multi-head Cross-attention Module, the Body Module of the Pre-trained LLM, and the BiLSTM. The Embedder module of the pre-trained LLM encodes the continuous task text prompt sequence into tokens $X_{tk} = (x_{tk1}, x_{tk2}, x_{tk3}, ..., x_{tkh})^T$, let $x_{tki} \in \mathbb{R}^{1\times D}$ denote the token embedding of the i-th unit in the task text prompt sequence, where D epresents the dimension of the token, and h represents the total number of units into which the task text prompt sequence is divided. In the Multi-head Cross-attention Module, the linearly mapped pre-trained word embeddings and the feature encodings and position encodings of the lithium-ion battery's historical charge-discharge features $X = (x_1, x_2, x_3, ..., x_L)^T$ undergo multimodal alignment through multi-head cross-attention. This results in the textual representation $X_{dk} = (x_{dk1}, x_{dk2}, x_{dk3}, ..., x_{dkL})$ of the lithium-ion battery's historical charge-discharge features, where $x_i \in \mathbb{R}^{L\times D}$ denotes the feature during the i_{th} charge-discharge, $x_{dki} \in \mathbb{R}^{L\times D}$ denotes the textual encoding feature during the i_{th} charge-discharge. In Body Module of Pre-trained LLM，In the Body Module of the Pre-trained LLM, the pre-trained LLM is used to extract features from X_{tk} and X_{dk} . Finally, the features extracted by the LLM, along with the historical charge-discharge data X of the lithium-ion battery, are used as inputs to the BiLSTM model to predict the SOH value of the lithium-ion battery for the next cycle.

2.2 Embedder Module of Pre-trained LLM

In this study, the LLM model selected is the Qwen2-0.5B model, a large language model based on the Transformer architecture. It incorporates advanced technologies such as the SwiGLU activation function, biased Q, K, V attention mechanisms, and grouped query attention. To adapt to the task of predicting the SOH of lithium-ion batteries, task-specific textual prompts must be provided to the LLM. The textual prompt content is illustrated in Figure 2.

[BEGIN Task Description]
***
[″role″:″system″,″content″]: You are an expert in the battery field specializing in battery life prediction and battery health prediction.
***
[″role″:″user″,″content″]:Predicting a specific value of S0H for the battery's future <*T*> discharges based on historical data from the battery's previous <*H*> charge/discharge cycles.
***
[″role″:″user″,″content″]:Accurately predicts the S0H value for the next <*T*> discharges of the battery.
[END Task Description]

Fig. 2. Task Prompt example

The Embedder Module of the Pre-trained LLM, as depicted in the corresponding module of Figure 1, first employs tokenization to split the task-specific textual prompts into discrete units such as words, phrases, or subwords. Subsequently, the Token Embedder converts these segmented units into real-number vectors, thus providing the model with learnable inputs. The formula for the task-specific textual prompts is as follows:

$$X_{tk} = Emb\_T(Tokenization(X_{text})) \tag{2.1}$$

where X_{text} represents the task-specific textual prompts, $Tokenization(.)$ denotes the tokenizer of the large model, $Emb\_T(.)$ stands for the Token Embedder of the Pre-trained LLM.

In addition to providing task-specific textual prompts to the LLM, this study also supplies the LLM with text-encoded information of historical charge-discharge data from lithium-ion batteries. This additional data further enhances the accuracy of the SOH prediction for lithium-ion batteries.

2.3 multi-head cross-attention Module

To achieve multimodal alignment and enable the LLM to comprehend and extract features from the historical charge-discharge data of lithium-ion batteries, this study first employs multi-head cross-attention to transform the historical charge-discharge data into Pre-trained Word Embeddings, and then use multi-head cross-attention to perform feature reconstruction on Y_{we} based on the correlation between the data features X during historical charge-discharge of lithium-ion batteries and the Pre-trained Word Embedding Y_{we}, achieving modal alignment between data and text. The calculation formula for multi-head cross-attention is as follows:

$$\begin{cases} q = linear(X) \\ k = linear(Y_{we}) \\ v = linear(Y_{we}) \end{cases} \tag{2.2}$$

$$head_i = Attention_i(Q_i, K_i, V_i) = Soft\max(\frac{q_i k_i^T}{\sqrt{d_{m_i}}})v_i \tag{2.3}$$

where q represents the vectors obtained from the historical discharge data of lithium-ion batteries after linear transformation. k and v are the vectors derived from the Pre-trained Word Embedding Y_{we} through different linear transformations. q_i, k_i and v_i are the i_{th} segments of q, k and after segmentation, respectively. d_{m_i} represents the dimension of the i_{th} segment vector, and $head_i$ represents the vector obtained from the cross-attention calculation of the i_{th} head. The formula for concatenating the vectors obtained from each head's cross-attention calculation is as follows:

$$X_{dk} = Concat(head_1, head_2, ...head_8) \tag{2.4}$$

where X_{dk} represents the text encoding of the historical charge-discharge data of lithium-ion batteries obtained after the multi-head cross-attention module.

In the multi-head cross-attention module, the historical charge-discharge data of lithium-ion batteries underwent multimodal alignment and transformation, providing learnable inputs for the LLM model. Subsequently, the Body Module of the Pre-trained LLM was employed to extract features from the aligned historical charge-discharge data.

2.4 Body Module of Pre-trained LLM

The Qwen2-0.5B LLM model selected in this study is a large language model based on the Transformer architecture. The Body Module of the Pre-trained LLM takes as input the task-specific text prompt encoding X_{tk} and the historical charge-discharge data of lithium-ion battery charge-discharge text encoding $Atten(Q,K,V)$, By utilizing the Pre-trained LLM, the model can better capture the intricate features and correlations in the lithium-ion battery charge-discharge process, including the subtle interactions among various variables such as voltage, current, and temperature. This enhances the accuracy and robustness of the prediction model. The formula for Body Module of Pre-trained LLM is as follows:

$$Y_{text} = LLM(X_{tk}, Atten(Q,K,V)) \tag{2.5}$$

where $LLM(.)$ represents the algorithm of the Body Module of the Pre-trained LLM, Y_{text} denotes the features of the historical charge-discharge data of lithium-ion batteries extracted by the LLM.

2.5 BiLSTM Module

To enhance the accuracy of predicting the SOH values of lithium-ion batteries, this study employs both text features Y_{text} and data features X as inputs to the BiLSTM model for predicting the future SOH values. The BiLSTM model, a variant of the recurrent neural network (RNN), overcomes the issue of gradient explosion present in traditional RNNs. By combining two unidirectional LSTM networks, the BiLSTM model simultaneously processes the forward and backward information of a sequence, effectively capturing long-distance dependencies within the sequence[10]. The structure of the BiLSTM neural network is illustrated in Figure 4, and the computation formula for each unidirectional LSTM network in BiLSTM is as follows:

$$\begin{cases} U = Concat(X, Y_{text}) \\ f_t = sigmoid\left(W_f\left[U_t, h_{t-1}\right] + b_f\right) \\ I_t = gigmoid\left(W_j\left[h_{t-1}, U_t\right] + b_j\right) \\ C_t = \tanh\left(W_c\left[h_{t-1}, U_t\right] + b_{i,c}\right) \\ C_t = f_t C_{t-1} + I_t C_t \\ O_t = sigmoid\left(W_o\left[h_{t-1}, x_t\right] + b_t\right) \\ h_t = O_t \tanh\left(C_t\right) \end{cases} \tag{2.6}$$

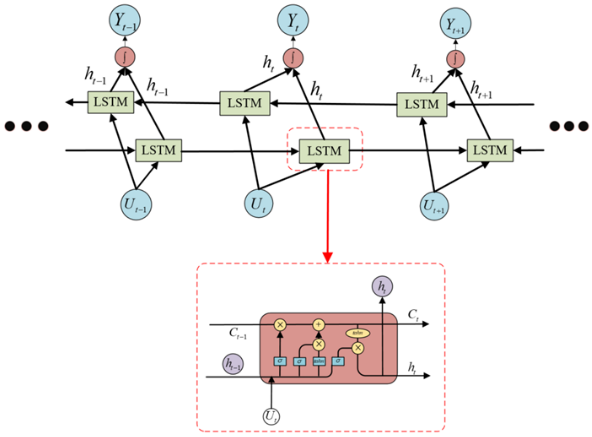

Fig. 4. Structure of BiLSTM

where U represents the new features obtained by combining the text features Y_{text} and the data features X , U_t is the input value at time step t , f_t constitutes the output of the forget gate at time step t ; I_t and $\tilde{C}_t$ constitute the output of the input gate at time step t ; O_t and h_t constitute the output of the output gate at time step t ; C_t and C_{t-1} represent the current and previous cell states, respectively. W_f 、 W_j 、 W_c 、 W_o denote the weight matrices corresponding to the forget gate, input gate, current cell state, and output gate, respectively, while b_f 、 b_j 、 b_c and b_t represent the respective bias vectors.

Ultimately, the hidden layer outputs of the two unidirectional LSTM networks are passed through a Fully Connected Neural Network (FCNN) to predict the future SOH values of the lithium-ion battery during charge and discharge cycles. The formula is as follows:

$$\begin{cases} K = Concat(Y_{text}, X) \\ Y_{out\_pre} = WK + b \end{cases} \tag{2.7}$$

where K represents the new features obtained by combining the text features Y_{text} and data features. W and b denote the weights and biases, respectively. Y_{out_pre} represents the predicted SOH value of the lithium-ion battery during charge and discharge cycles.

2.6 State of health estimation algorithm based on LLM-BiLSTM model

The proposed LLM-BiLSTM model employs cross-attention for multimodal alignment, transforming the charge and discharge data of lithium batteries into text encoding. To enhance the LLM's understanding of the task objective, task-specific textual prompts are input into the LLM and subsequently tokenized and encoded. The Body

Module of the Pre-trained LLM is then utilized for text feature extraction. Finally, considering both the text features extracted by the Body Module and the charge-discharge data features, the BiLSTM predicts the SOH of the lithium batteries. The training and testing processes of the LLM-BiLSTM model are illustrated in Table 1.

Table 1. LLM-BiLSTM modeling algorithm

Algorithm: the training algorithm for the LLM-BiLSTM model
Input: The text task description X_{text}, the historical charge-discharge features of the lithium-ion battery $X=(x_1,x_2,x_3,...,x_L)^T$ and SOH values $Y_{out}=(y_1,y_2,y_3,...,y_L)^T$
Output: The SOH value for the next charge-discharge cycle of the lithium-ion battery
Parameters: Maximum number of iterations :epoch; Training batch size :B; Learning rate: lr.
Training process：
1：Random initialization: randomly initialize the weight parameter matrix and bias of the LLM-BiLSTM model θ_w and θ_b.
2：Packed datasets: making small batches $\{X_b\}_{b=1}^{B}$ and $\{Y_{out\_b}\}_{b=1}^{B}$.
3：repeat
4： for b=1 to B do
5： Input X_b into the LLM-BiLSTM model to obtain the SOH prediction Y_{out_pre}， Then input Y_{out_b} and Y_{out_pre} into the loss function to get the loss.
6： Inverse update θ_w and θ_b by minimizing the loss function value.
7： end for
8：until reach maximum number of iterations epoch
Testing process：
9：for b=1 to B do
10：Input $testX_b$ and $testZ_b$ into the LLM-BiLSTM model, obtain the SOH prediction Y_{out_pre}.

3 Experimental Simulation Result and Analysis

The dataset used in this study is derived from a foreign research laboratory and involves the cyclic aging of commercial 21700 cylindrical cells (LG M50T, LG GBM50T2170) under three different temperatures and four different SOC levels $(0\%-30\%$, $70\%-85\%$, $85\%-100\%$, $0\%-100\%)$ [11]. The experimental conditions chosen for this study involve cyclic aging within a specified SOC range, as detailed in Table 2.

Initially, the battery activation is performed by charging at a constant current of 0.3C until the voltage reaches 4.2V, followed by constant voltage charging at 4.2V until the current drops below 0.01C, and then resting until the battery capacity is 250mAh. After meeting the cyclic experiment requirements, the battery undergoes 77 continuous charge-discharge cycles before being rested. This procedure is repeat-ed after a period to acquire the charge-discharge data features of the selected lithium batteries.

Table 2. Lithium-Ion Battery Cyclic Aging Experimental Procedure Table

Step	Control Type	Control Value	Primary Limits
1	CC charge	0.3C	$E_{cell} = 4.2V$
2	CV charge	4.2V	$\lvert I \rvert < C/100$
3	Rest	Rest at OCV	$time = 4h$
4	CC discharge	1C	$E_{cell} = 2.5V$
5	CC charge	0.3C	$E_{cell} = 4.2V$
6	CV charge	4.2V	$\lvert I \rvert < C/100$
7	Loop to step	N/A	77times

3.1 Data preprocessing

Data normalization is a crucial step in data preprocessing, aiming to convert data from different ranges into a unified standard range. This process eliminates the differences in dimensions and value ranges among different features, ensuring comparability and preventing any single feature from disproportionately influencing the model training. It also helps accelerate the convergence of algorithms and enhances model stability.

Given that factors such as battery voltage, current, temperature, capacity, and cycle count have different magnitudes and units, it is essential to standardize these data when estimating battery health status. In this study, these factors are normalized to fall within the range of 0 to 1.

The method for data normalization is as follows:

$$X_N = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3.1}$$

where x represents the original input data, $x_{\min}$ is the minimum value of the original input data feature, $x_{\max}$ is the maximum value of the original input data feature, X_N is the normalized data.

Additionally, large models based on the Transformer architecture process token sequences in parallel rather than sequentially. This parallel processing approach treats all tokens equally, which can prevent the model from capturing the temporal information of the input sequence. To address this issue, this method introduces positional encoding to encode both absolute and relative positions of the input sequence. This encoding approach provides a unique positional encoding for each time step and establishes a bounded encoding range.

The absolute positions in the positional encoding sequence are represented using sine and cosine functions. These functions' products provide the relative positions. The vectors for each positional encoding alternate between $\sin$ and $\cos$ values, as follows:

$$\begin{cases} PE_{pos,2i} = \sin\left(\dfrac{pos}{10000^{\frac{2i}{d_{model}}}}\right) \\ PE_{pos,2i+1} = \cos\left(\dfrac{pos}{10000^{\frac{2i}{d_{model}}}}\right) \end{cases} \tag{3.2}$$

where pos represents the position index within the input sequence. Each element in the positional encoding vector is indexed by i , and the dimension of the positional encoding vector is denoted by d_{model} .

3.2 Results and Discussion

This study utilizes metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination(R^2) to evaluate the model's performance[12]. The calculation methods for these metrics are as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i\right| \tag{3.3}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2 \tag{3.4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y}_i - y_i)^2} \tag{3.5}$$

where n is the number of prediction samples, y_i represents the actual SOH values, and y_i denotes the predicted SOH values.

To validate the effectiveness of the proposed method, this study employs the aforementioned three key statistical metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Coefficient of Determination (R^2). Using these evaluation metrics, we compared the performance of the proposed LLM-BiLSTM model against the basic Bidirectional Long Short-Term Memory (BiLSTM) model and the GRU model. Table 4 presents the three models along with their respective evaluation metrics. As observed in the table, the LLM-BiLSTM model demonstrates superior accuracy and computational efficiency compared to the BiLSTM and GRU models. Specifically, the LLM-BiLSTM model achieves the lowest MAE and MSE values, 0.003307 and 0.004201 respectively , and the highest R^2 value of 0.9917, indicating a better prediction performance than the other models.

Table 4. Comparison of several models' prediction mistakes

Model	MAE	MSE	R^2
LLM-BiLSTM	**0.003307**	**0.004201**	**0.9917**
GRU	0.005215	0.006131	0.9819
BiLSTM	0.007093	0.008603	0.9726

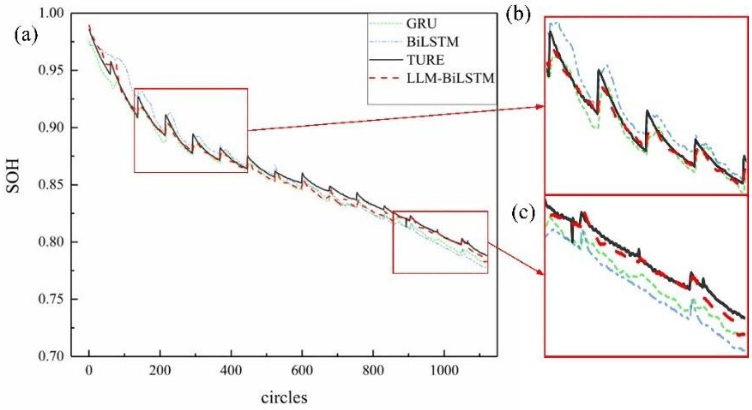

Fig. 5. Lithium-ion battery charge/discharge SOH predictions

The one-step prediction results for battery health status are shown in Figure 5. The results indicate that the predicted values of the LLM-BiLSTM model are closest to the actual values, while the BiLSTM model shows the poorest predictive performance. The superior performance of the LLM-BiLSTM model can be attributed to the use of a large model and multimodal information. Large models, when properly regularized and pre-trained, generally exhibit better generalization capabilities when dealing with diverse types and conditions of battery data. Moreover, by integrating multimodal information, the LLM-BiLSTM model can reduce the uncertainty and errors associated with a single data source, thereby more effectively capturing the complex dynamic characteristics of lithium battery performance degradation. Consequently, the LLM-BiLSTM model provides more accurate predictions compared to other models.

4 Conclusion

This paper proposes a multimodal fusion-based LLM-BiLSTM model for SOH estimation of lithium batteries. First, a cross-attention mechanism is employed to reconstruct the charge-discharge data into text form, aligning the data and text modalities to provide a more comprehensive and accurate information representation. Tokenization and encoding are then used to extract features. The pre-trained LLM model processes the input encodings and the features reconstructed through cross-attention. Finally, the features extracted by the LLM model, along with the charge-discharge data of the lithium batteries, are input into the BiLSTM for SOH prediction. This study utilizes cyclic aging data from Commercial 21700 cylindrical cells. Under the same conditions, the proposed model outperforms the BiLSTM and GRU models in prediction accuracy.

The proposed model possesses robust nonlinear feature extraction capabilities, capable of capturing hidden patterns and trends within complex charge-discharge curves, significantly improving the accuracy and robustness of SOH prediction for lithium batteries. Future research could focus on reducing computational complexity and more accurately predicting the initial SOH values after each rest period, thereby enhancing the safety and reliability of energy storage systems.

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