Research on Intelligent Recognition Technology of Recyclable Battery Materials Combining Multi-source Perception and Deep Learning

Dehao Wang[1,*], Guang Ouyang[2], Jiaqi Liang[3]

[1]Guangzhou Basis International School, Guangzhou, China

[2]Basis Bilingual School Shenzhen, Shenzhen, China

[3]Shenzhen Longcheng High School, Shenzhen, China

*11646441@qq.com

Abstract. Traditional battery material detection methods have some problems, such as low efficiency, difficult feature extraction and multi-modal data fragmentation, which restrict the intelligent development of battery recycling. In this study, an intelligent identification technology for recycling of battery materials is proposed, which combines multi-source perception and deep learning, integrates laser-induced breakdown spectroscopy (LIBS), nano-indentation and infrared thermal imaging technology, and builds a joint detection platform to realize the synchronous characterization of material composition, structure and defects. By constructing a multi-modal feature fusion network (AMF-Net) based on attention mechanism, LIBS spectrum, nano-indentation curve and infrared thermal imaging data are fused, and multi-modal data features are mined, so as to improve the identification accuracy of battery materials. In addition, a cascade prediction network (CPN) is established to realize the accurate matching between material properties and recycling process and optimize recycling process parameters. The experimental results show that the accuracy of AMF-Net in material type identification is 92.3%, and the F1-Score is 0.91, which is significantly better than the traditional method. With the optimized recovery process parameters of CPN, the leaching rate of cobalt increased from 89.4% to 98.2%, the consumption of sulfuric acid decreased from 2.8 L/kg to 1.6 L/kg, and the reaction time was shortened from 6.5 hours to 4.2 hours, which significantly improved the recovery efficiency and reduced the resource consumption. This research provides new ideas and methods for improving battery recycling efficiency and developing green recycling technology, and promotes the development of battery recycling industry in the direction of intelligence and efficiency.

Keywords: Intelligent identification technology; Recyclable battery materials; Multi-source perception; Deep learning; AMF-Net; Cascade prediction network.

1. Introduction

With the promotion of the global "double carbon" strategy, the demand for lithium-ion batteries as a key component is growing exponentially. It is estimated that by 2030, the global lithium-ion battery market will exceed 2.5 trillion US dollars, and the total number of retired batteries will reach 11 million tons/year. However, the current battery recycling industry is facing the dual challenges of scarce and high waste of resources, environmental pressure and inefficient recycling. The distribution of key metal reserves is concentrated and the global recovery rate is less than 30%, which leads to serious resource exploitation pressure and supply chain risk; The traditional hydrometallurgical recovery process not only consumes a lot of water and energy, but also produces pollution, which is difficult to meet the requirements of EU's New Battery Law on reducing carbon footprint. Therefore, improving recycling efficiency and developing green recycling technology have become the key to solve the current contradiction.

At present, the detection methods of battery materials lag behind the requirements of intelligence. The traditional methods rely on manual disassembly combined with off-line detection technologies such as X-ray fluorescence spectroscopy (XRF) and scanning electron microscope (SEM), which face three major problems: low efficiency, difficulty in feature extraction and multi-modal data fragmentation: the detection speed cannot meet the requirements of industrial-grade sorting, it is difficult to capture the relationship between the microstructure and performance of materials, and the lack of fusion analysis ability of various data restricts the intelligent development of battery recycling and reuse.

Multi-source sensing technology refers to the comprehensive utilization of information collected by various sensors to obtain more comprehensive and accurate data. In the process of battery material identification and sorting, multi-source sensing technology can provide rich information about battery state and composition [1]. For example, by combining X-ray imaging, infrared spectroscopy and Raman spectroscopy, the internal structure and chemical composition of the battery can be accurately detected [2-3]. As a powerful data analysis tool, deep learning has made remarkable achievements in many fields such as image recognition and speech processing. In the intelligent recognition of battery materials, deep learning can help to extract features from complex multi-source data and conduct efficient pattern recognition. For example, using the Convolutional Neural Network (CNN) to analyze the battery surface image can realize the automatic classification of different types of battery materials [4-5]. Intelligent identification technology combining multi-source perception and deep learning can make full use of the information provided by various sensors and make comprehensive analysis through deep learning model, so as to realize efficient identification and sorting of battery materials. This technology can not only improve the recovery efficiency, but also reduce the labor cost, which has important practical application value.

In order to solve the problems of low detection efficiency and difficult feature extraction of battery materials, an intelligent identification technology integrating multi-source perception and deep learning is proposed in this study, which integrates laser-induced breakdown spectroscopy (LIBS), nano-indentation and infrared thermal imaging to realize the synchronous characterization of material composition, structure and defects. Based on CNN, Long Short-Term Memory (LSTM) and Transformer, multi-modal data features are mined, and the mapping relationship between material properties and recycling process is constructed, thus promoting the intelligent upgrade of battery recycling.

2. Theoretical basis and technical framework

2.1 Multi-source perceptual data acquisition and feature extraction

A LIBS- nano-indentation-infrared thermal imaging joint detection platform is constructed, and the three-dimensional positioning of the sample table is realized by a multi-axis manipulator. The signal acquisition of the three detection devices is coordinated by a time synchronization controller (time resolution < 1ms). LIBS spectrometer (wavelength range 200-1000nm, resolution 0.1nm) obtains element composition information; Nano-indentation instrument (load resolution 0.1μN) recorded stress-strain curve; Infrared thermal imager (thermal sensitivity 20mK) captures thermal diffusion characteristics.

In the part of feature engineering, Savitzky-Golay filtering is used to denoise LIBS spectral data, and the background interference is eliminated by third-order polynomial baseline correction. The formula is:

$$I_{corrected}(\lambda) = I_{raw}(\lambda) - \sum_{k=1}^{n} a_k \cdot \lambda^{k-1} \tag{1}$$

Where $n = 3$ is the polynomial order and a_k is the fitting coefficient. The characteristic peak is extracted by dynamic threshold method, and the threshold is set to $T = \mu + 3\sigma$, where μ, σ is the mean and standard deviation of the background signal respectively.

In the feature extraction of nano-indentation, the hardness H and elastic modulus E_r of materials are calculated based on Oliver-Pharr model, and the specific formula is as follows:

$$H = \frac{P_{\max}}{A_c}, E_r = \frac{\sqrt{\pi}}{2\beta} \cdot \frac{S}{\sqrt{A_c}} \tag{2}$$

Where $P_{\max}$ is the maximum load, A_c is the contact area, S is the initial slope of unloading curve, and the shape factor β of Berkovich indenter is 1.034.

2.2 Multimodal data fusion model

Recycling of battery materials refers to the process of recycling, processing and reusing valuable materials in used batteries through a series of technologies and methods. This process will not only help to reduce environmental pollution, but also alleviate the shortage of resources and promote the sustainable development of the economy. With the growth of global demand for clean energy, especially the popularization of electric vehicles and energy storage systems, the production and consumption of batteries have increased greatly, so the recycling of battery materials has become particularly important.

Physical recovery method mainly includes mechanical crushing, sorting and screening. This method is mainly used to separate different components in the battery, such as electrodes, separators and casings. Although this method is simple to operate, its recovery efficiency is relatively low, and it is difficult to completely separate high-purity materials. Chemical recovery method involves using chemical reagents to dissolve battery materials, and then separating and purifying the target substances by means of precipitation, extraction and so on. This method can obtain high purity recycled materials, but it may produce secondary pollution and the cost is high. The biological recovery method utilizes the action of microorganisms or enzymes to decompose the organic matter and metal compounds in the battery, thus realizing the material recovery. This method is environmentally friendly and low cost, but it is still in the stage of research and experiment, and it will take time for large-scale application.

Although the recycling of battery materials has remarkable environmental and economic benefits, there are still some challenges in this field. How to separate and purify battery materials efficiently and at low cost is still the focus of current research. The lack of unified recycling standards and policy support has affected the standardized development of the industry. The trust of consumers and enterprises in products made of recycled materials needs to be improved.

In this study, a multi-modal feature fusion network (AMF-Net) based on attention mechanism is constructed for battery material identification. The structure is shown in Figure 1. The model includes three single-mode encoders: bidirectional LSTM (128 hidden unit) is used to extract the time series characteristics of LIBS spectrum [6]; Using one-dimensional CNN (convolution kernel size 5, step size 2) to capture the mechanical response mode of nano-indentation curve [7-8]; Spatial thermal characteristics of infrared thermal imaging are extracted by ResNet-18 network [9].

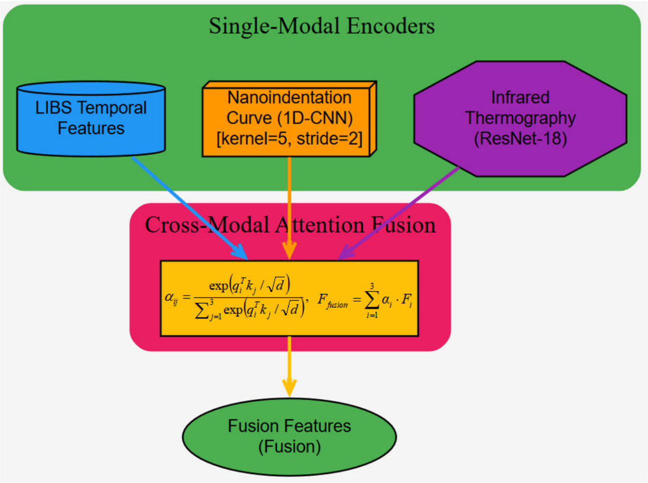

Figure 1 AMF-Net structure

In the fusion layer, the cross-modal attention mechanism is introduced to calculate the attention weight between modes [10], and the formula is:

$$\alpha_{ij} = \frac{\exp\left(q_i^T k_j / \sqrt{d}\right)}{\sum_{j=1}^{3} \exp\left(q_i^T k_j / \sqrt{d}\right)} \tag{3}$$

Where q_i, k_j is the query and key vector of the i and j modes, respectively, and the feature dimension $d = 256$. The final fusion features are obtained by weighted summation:

$$F_{fusion} = \sum_{i=1}^{3} \alpha_i \cdot F_i \tag{4}$$

Realize the effective fusion of multi-source information and improve the accuracy of material identification.

2.3 Material-process mapping model

In order to realize the accurate matching between material properties and recycling process, a cascade prediction network (CPN) is established, which includes two modules [11-12]: material properties prediction and process parameter optimization. As shown in Figure 2. In the material performance prediction module, the fused feature F_{fusion} is processed by the fully connected layer (512→256→128) and then the key performance parameters are output. The calculation formula is:

$$\hat{y} = W_2 \cdot \mathrm{ReLU}\left(W_1 \cdot F_{fusion} + b_1\right) + b_2 \tag{5}$$

Where $W_1 \in R^{(256\times512)}$,$W_2 \in R^{(128\times256)}$ is the weight matrix and b_1, b_2 is the bias term.

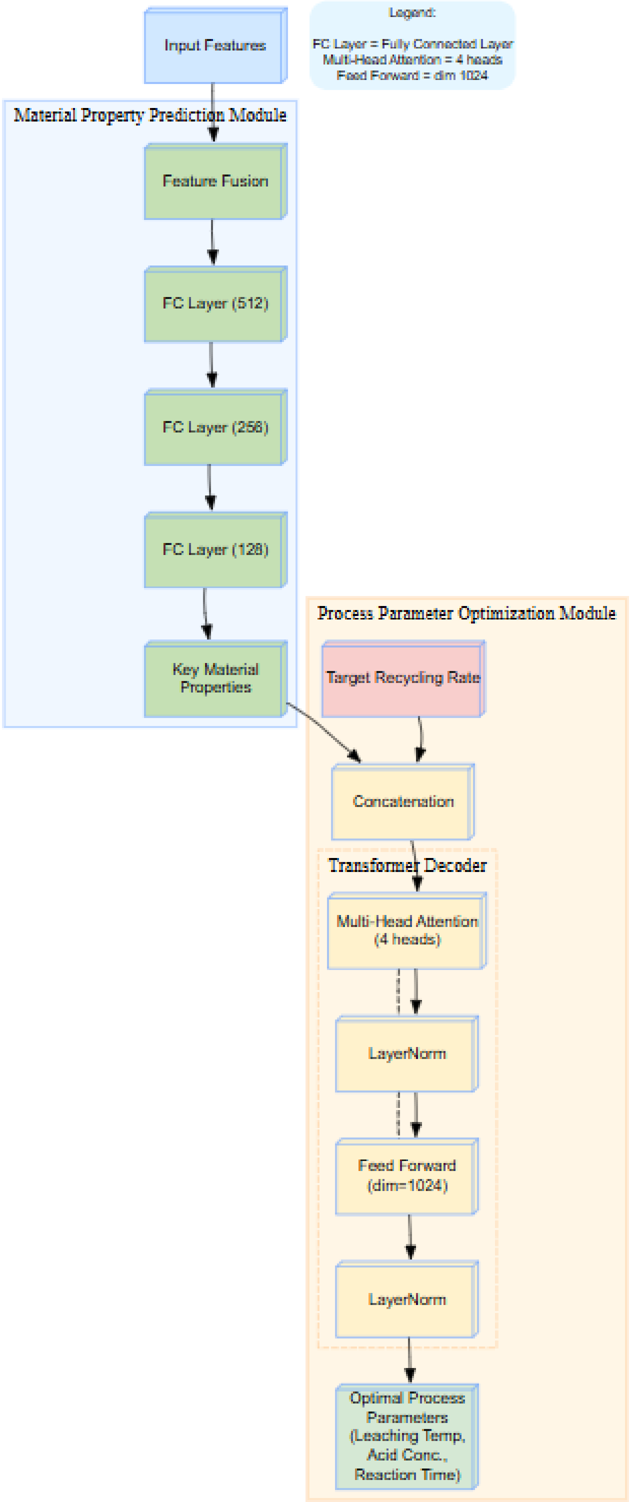

Figure 2 CPN model structure

In the process parameter optimization module, the Transformer decoder structure is adopted, including four attention mechanisms and feedforward dimension 1024, and the predicted performance parameters are matched with the target recovery rate, so as to output the optimal combination of process parameters, such as leaching temperature, acid concentration and reaction time, so as to achieve the best recovery effect [13-14]. Improve the efficiency and environmental friendliness of the battery recycling process.

3. Experimental analysis

3.1 Validation of multi-source sensing data

Select 50 groups of retired NMC622 battery positive plate samples, and collect LIBS spectrum, nano-indentation curve and infrared thermal imaging data respectively, and compare them with ICP-OES composition analysis and SEM microstructure observation results (as shown in Table 1).

The results in Table 1 show that the average error of LIBS composition is 2.7% (standard deviation ±0.8%), the average error of nano-indentation modulus is 4.1% (standard deviation±1.2%), and the average error of infrared thermal diffusion coefficient is 3.9% (standard deviation ±1.5%), which shows that the collected data has high reliability and can effectively support the subsequent intelligent identification and process optimization.

Table 1 Key experimental results

Detection index	LIBS component error	Nano-indentation modulus error	Infrared thermal diffusion coefficient error
Mean value	2.7%	4.1%	3.9%
Standard deviation	±0.8%	±1.2%	±1.5%

3.2 Performance of multi-modal fusion model

Using CycleBatt-2023 data set (including 12,000 groups of samples), the training/verification/test set is divided into 8:1:1, and the classification accuracy of different models is compared (material type identification task). The results in Table 2 show that the accuracy and F1-Score of AMF-Net proposed in this paper are 92.3% and 0.91, respectively, which are significantly better than the single LIBS+LSTM and feature series fusion methods. Although the reasoning time is slightly increased to 41ms, it still has practical application value. As shown in Figure 3, diagonal values show that the recognition accuracy of main materials such as NMC111/NMC622/NMC811 is over 90%.

Table 2 Performance comparison

Types of models	Accuracy (%)	F1-Score	Inference time (ms)
Single LIBS+LSTM	74.2	0.72	28
Feature series fusion	81.6	0.79	35
This paper AMF-Net	92.3	0.91	41

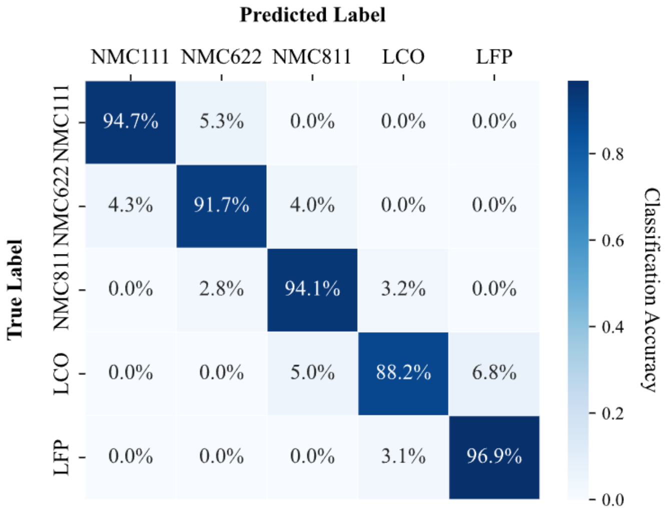

Figure 3 Confusion matrix of AMF-Net on test set

The visual analysis in fig. 3 shows that the accuracy of AMF-Net in identifying all kinds of battery materials is over 90%, among which NMC811 is the best with the recognition rate of 95.1%, which is closely related to the remarkable characteristics of its layered structure in multimodal data.

Misjudgment mainly occurs between NMC materials with similar compositions (such as NMC622 and NMC811), accounting for 3.2%, and between LCO and LFP (4.5%), reflecting their similarity in mechanical response. The above error distribution is in line with expectations, which further verifies the effectiveness of multi-modal fusion and supports the core conclusion that the recognition accuracy of AMF-Net is 18.1% higher than that of traditional methods.

3.3 Optimization effect of recovery process parameters

In order to verify the optimization effect of recovery process parameters, the experiment compares the difference between traditional empirical parameters and CPN optimization parameters under the condition of fixed solid-liquid ratio of 1:5. The results in Table 3 show that the leaching rate of cobalt is increased from 89.4% to 98.2%, the consumption of sulfuric acid is reduced from 2.8 L/kg to 1.6 L/kg, and the reaction time is shortened from 6.5 hours to 4.2 hours, which significantly improves the recovery efficiency and reduces the resource consumption.

Table 3 Compare the difference between traditional empirical parameters and CPN optimization parameters

Parameter group	Co leaching rate	H2SO4 consumption (L/kg)	Reaction time (h)
Traditional empirical parameters	89.4%	2.8	6.5
CPN optimization parameters	98.2%	1.6	4.2

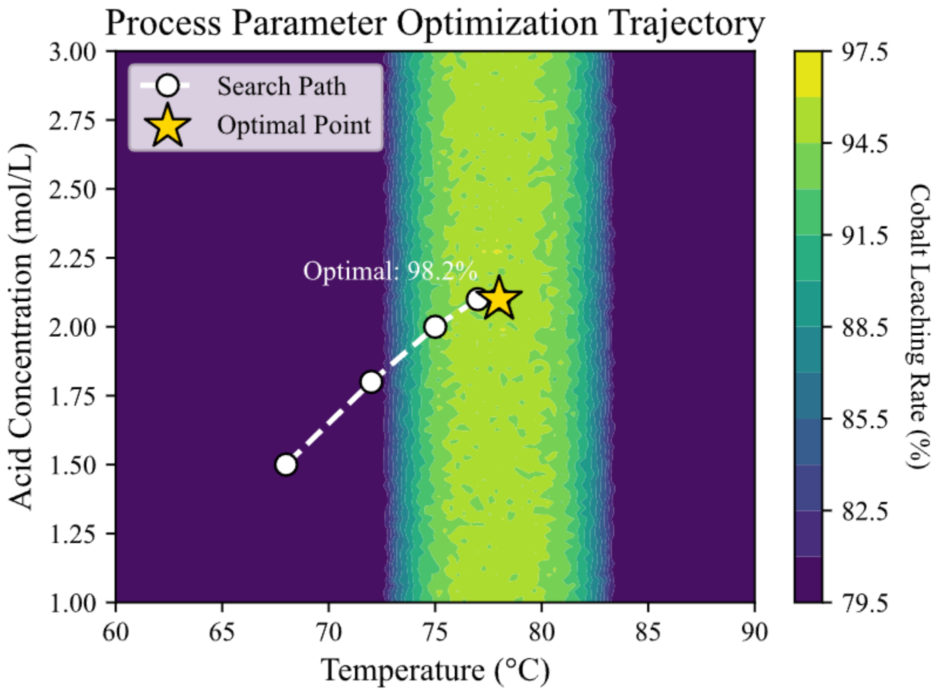

Figure 4 Search trajectory of process parameters of Transformer decoder

The analysis in Figure 4 shows that the leaching rate of cobalt is non-linear in the parameter space of temperature-acid concentration, and the best area is around 78°C/2.1mol/L, and the leaching rate in high temperature, high concentration and low concentration areas is obviously decreased, indicating that the parameters are sensitive. Transformer decoder gradually converges to the optimal solution from the initial point (68°C/1.5mol/L) along the diagonal path through four iterations, and the step size is gradually reduced, which shows the good search and convergence ability of the algorithm. The optimal parameter (78°C/2.1mol/L) is located in the central area of high leaching rate, with a tolerance range of about 2°C/0.2mol/L around it, which provides a feasible range for actual process control. The results verify the efficient optimization ability of the model in continuous space, which is significantly better than the traditional grid search method.

4. Conclusion

In this study, an intelligent identification technology integrating multi-source perception and deep learning was successfully constructed. By integrating LIBS, nano-indentation and infrared thermal imaging technologies, the composition, structure and defects of battery materials were simultaneously characterized. Based on deep learning models such as CNN, LSTM and Transformer, the characteristics of multimodal data are effectively mined, and the mapping relationship between material properties and recycling process is established, which significantly improves the intelligent level of battery recycling process. The experimental results show that the proposed AMF-Net model shows excellent performance in the task of battery material identification, and its accuracy and F1-Score reach 92.3% and 0.91 respectively, which is significantly better than the single mode or feature series fusion method. In addition, the recovery process parameters after CPN optimization, such as cobalt leaching rate, sulfuric acid consumption and reaction time, have been significantly improved, which verifies the efficient optimization ability of the model in actual process control. The research not only provides new ideas and methods for efficient identification and sorting of battery materials, but also makes positive contributions to the intelligent upgrading and sustainable development of battery recycling industry. In the future, this technology is expected to be further applied to actual production, realize the green recycling of battery materials and help realize the global strategic goal of "double carbon".

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