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A Study on the Life Prediction of Lithium Ion Batteries Based on a Convolutional Neural Network Model

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Abstract

Recently, green energy support policies have been announced around the world in accordance with environmental regulations, and as the market grows rapidly, demand for batteries is also increasing. Therefore, various methodologies for battery diagnosis and recycling methods are being discussed, but current accurate life prediction of batteries has limitations due to the nonlinear form according to the internal structure or chemical change of the battery.

In this paper, CS2 lithium-ion battery measurement data measured at the A. James Clark School of Engineering, University of Marylan was used to predict battery performance with high accuracy using a convolutional neural network (CNN) model among deep learning-based models. As a result, the battery performance was predicted with high accuracy. A data structure with a matrix of total data 3,931 X 19 was designed as test data for the CS2 battery and checking the result values, the MAE was 0.8451, the RMSE was 1.3448, and the accuracy was 0.984, confirming excellent performance.

Keywords: Waste battery, electric vehicles, convolutional neural network, Impedance, Lithium-Ion Battery

1. Introduction

As markets such as electric vehicles (EVs) and energy storage systems (ESSs) expand domestically and internationally thanks to government policies, demand for batteries is increasing. It is expected that lithiumion waste batteries, which deteriorate over time, will be poured out. In particular, as electric vehicles are rapidly activated for reasons such as carbon neutrality and environmental improvement, the frequency of accidents, breakdowns, and scrapping occurring after vehicle operation is expected to increase. Therefore, it is necessary to efficiently operate waste batteries in terms of safety and environment. The importance of the collection and storage of discharged batteries, including issues of disposal and recycling, is increasing [1-2].

For a safe and efficient electric vehicle recycling and treatment method, battery life prediction is essential, but it seems impossible to apply the existing battery diagnosis system. Currently, a method of predicting the life of a battery and determining the state by checking the state of charge (SOC) of the battery through a battery management system (BMS) is mainly used. This method has low accuracy and needs to be improved in terms of safety. Therefore, life prediction methods of electric vehicle batteries that are different from the existing methods should be proposed and applied. This paper aims to predict the lifetime of CS2 lithium-ion battery

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measurement data using a convolutional neural network (CNN) model among deep learning-based models, and to check and evaluate how accurate it is [3-4].

2. Design of CNN-based model for predicting battery life

In this study, the battery capacity decrease trend is confirmed by normalizing the voltage, current, and usage of the battery among the various columns of the data set. 80% of the data set is a training data set and 20% is used as a test data set to predict battery life. The convolutional neural network (CNN) to be used is a structure that imitates the structure of the human optic nerve and extracts features from data to identify patterns from those features. Feature extraction identifies features by examining the adjacent components of each component in the data. The features derived here are abstracted and compressed into a specific layer, and the size of the layer derived in this way is reduced. In the process of reducing the data size, it proceeds through the process of removing noise and creating uniform features. It extracts the learned features by sharing the weight and can be effectively applied to the battery diagnosis method because it is not affected by the size of the input [4].

Figure 1 shows the training process for estimating the SOH of a lithium-ion battery based on the CNN model. For SOH estimation, the structural design consists of a total of 5 convolutional layers and 3 fully connected layers, which are used for classification work on data.

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		Input	(None, 4, 4, 256)		
			(None, 2, 2, 256)		

conv2d_7 (Conv2D)	Input	(None, 2, 2, 256)				
	output	(None, 2, 2, 512)				
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max_pooling2d_7	Input	(None, 2, 2, 512)				
(MaxPooling 2D)	output	(None, 1, 1, 512)				
flatten 1 (Elatten)	Input	(None, 1, 1, 512)				
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dance 2 (Dance)	Input	(None, 512)				
dense_2 (Dense)	output	(None, 128)				
d	Input	(None, 128)				
dense_2 (Dense)	output	(None, 64)				
dense_3 (Dense)	Input	(None, 64)				
	output	(None, 10)				

Figure 1. Design of CNN model structure for SOH estimation

This paper aims to predict the remaining life and health of lithium-ion batteries through Convolution Neural Network (CNN), one of the most widely used deep learning-based models to predict the lifespan of waste lithium-ion batteries. For the evaluation of the models, measurement data of the CS2 lithium-ion battery measured at the College of Engineering at the University of Maryland, USA were used. It implements a convolutional neural network and uses TensorFlow and Keras for data classification.

3. MAE and RMSE analysis of the data applied to CNN model

MAE and RMSE are important indicators for evaluating the predictive performance of a model. In Figure 2, Instances represent individual data points or samples in the dataset, and the graph visualizes the MAE for each data point using values representing the order of data instances on the x-axis. Each value on the x-axis represents the order of an individual data point in the dataset, and the MAE value for each data point is represented on the y-axis [5].

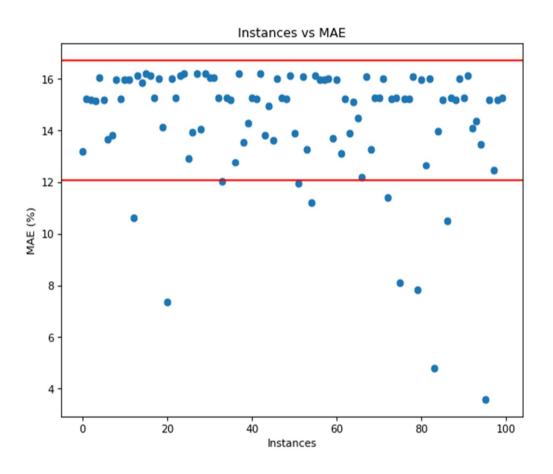


Figure 2. Visualize the relationship of Instances vs MAE

4. Conclusion

For the SOH estimation of the CS2 lithium-ion battery based on the CNN model, the structural design consists of a total of 5 Convolutional Layers and 3 Fully Connected Layers. This structure is used to classify the data. The structure of the CNN model presented here is designed to solve the data classification problem and consists of a total of 13 layers [6].

Pseudocode that performs data set separation, CNN model creation, model learning, model evaluation,

prediction, and classification model evaluation is implemented. As shown in Table 1, the MAE was 0.8451, the RMSE was 1.3448, and the accuracy was 0.984. The operating battery requires additional data sets depending on the type and characteristics, but using the implemented model, it will be possible to predict battery performance with a high safety of 98% or more [7].

Model	MAE	RMSE	Accuracy
CNN	0.8451	1.3448	0.984

Table 1. CNN model-based life expectancy result

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