Hybrid deep learning for estimation of state-of-health in lithium-ion batteries

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ABSTRACT

Lithium-ion (li-ion) batteries have a high energy density and a long cycle life. Lithium-ion batteries have a finite lifespan, and their energy storage capacity diminishes with use. In order to properly plan battery maintenance, the state of health (SoH) of lithium-ion batteries is crucial. This study aims to combine two deep learning techniques (hybrid deep learning), namely convolutional neural network (CNN) and bidirectional long short-term memory (BiLSTM), for SoH estimation in li-ion batteries. This study contrasts hybrid deep learning methods to single deep learning models so that the most suitable model for accurately measuring the SoH in lithium-ion batteries can be determined. In comparison to other methodologies, CNN-BiLSTM yields the best results. The CNN-BiLSTM algorithm yields RMSE, mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) in the following order: 0.00916, 0.000084, 0.0048, and 0.00603. This indicates that CNN-BiLSTM, as a hybrid deep learning model, is able to calculate the approximate capacity of the lithium-ion battery more accurately than other methods.

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1. INTRODUCTION

Lithium-ion (li-ion) batteries have a high energy density and a long cycle life [1]. Lithium-ion batteries can optimize energy utilization from solar panels and provide a reliable energy supply when it is needed [2]. However, lithium-ion batteries have a restricted shelf life and experience a decline in energy storage capacity over time and use [3]. This can influence the performance of the equipment and the battery life. State of Health estimation on lithium-ion batteries increases battery utilization efficiency as a result. Estimating the state of health (SoH) of lithium-ion batteries can be accomplished using a variety of techniques, such as battery sensors, mathematical models, visual methods, and deep learning methods based on battery management technology [4], [5]. Deep learning offers more accurate estimates of SoH and remaining useful life (RUL) than the other methods and enables systems to monitor the state of the battery in actual time [6].

Previous research has utilized deep learning for battery health estimation using methods such as convolutional neural network (CNN) [7], long short-term memory (LSTM) [8], Bidirectional LSTM (BiLSTM) [9], and deep belief networks (DBNs) [10]. Prior studies only employed a single deep learning technique, which lacked generalization capabilities and was dependent on training data, resulting in overfitting. This new research combines CNN and BiLSTM for Li-ion battery SoH estimation in order to provide more accurate results by utilizing the strengths of both methods. Hybrid deep learning can overcome generalization problems and reduce overfitting caused by training data dependence, thereby increasing estimation accuracy [11].

This study's objective is to employ hybrid deep learning techniques to estimate the SoH of lithium-ion batteries. The hybrid deep learning method utilized in research is a combination of CNN and BiLSTM. CNN has the ability to process data with a large number of features and capture complex patterns and relationships between features on battery data [12]. CNN, however, is limited in its ability to analyze sequential data correlations and time-related data relationships. In contrast, BiLSTM has an advantage for overcoming CNN's limitations in that it can analyze sequential data correlations and time relationships within data [13]. This research contributes to combining CNN and BiLSTM to leverage the strengths of both methods, with the expectation of producing a hybrid deep learning method that is more powerful and more accurate for measuring the SoH of lithium-ion batteries. This research also compares the performance of hybrid deep learning and single deep learning in order to determine the optimal model for estimating SoH in lithium-ion batteries.

Previous research has developed an estimate of the state of health (SoH) for lithium-ion batteries. Duan *et al.* [14] compared the machine learning techniques k-nearest neighbors (K-NN), logistic regression (LR), ensemble learning (EL), and support vector machine (SVM). These research results demonstrate that the EL method is more effective than other methods. Furthermore, the estimation of SoH in lithium-ion batteries using deep learning is growing. Jo *et al.* [15] compared the CNN, feedforward neural network (FNN), and long short-term memory (LSTM) and found that the LSTM method performed better than the other methods. Jia *et al.* [16] estimates SoH and RUL using Gaussian process regression (GPR) and produces good predictions of estimation accuracy. Khan *et al.* [17] compared adaptive boosting (AB), support vector regression (SVR), LSTM, multi-layer perceptron (MLP), bi-directional LSTM (BiLSTM), and CNN and resulted in the BiLSTM method being the best method compared to other methods. However, these studies have limitations in measuring the SoH of lithium-ion batteries using only one selected machine learning or deep learning method.

Combining deep learning methods (hybrid deep learning) can be used to improve the accuracy of SoH estimation [18], [19]. The hybrid CNN-LSTM model utilized in study [20] proved superior to either CNN or LSTM. BiLSTM is an evolution of the LSTM paradigm, so BiLSTM always produces superior results. CNN is unable to analyze sequential correlations and temporal relationships in data. BiLSTM has the benefit of being able to examine data sequential correlations and intertemporal relationships. CNN and BiLSTM can provide more accurate estimates of lithium-ion battery SoH when used together.

2. MATERIAL AND METHODS

This study estimates the SoH in Lithium-Ion batteries using hybrid deep learning. The research uses five stages of method: data preprocessing, data modeling, hyperparameter tuning, and evaluation. The explanation of each method is as follows.

2.1. Dataset

The study utilized data from the NASA prognostics data repository [21], [22]. The data includes experimental information about the lithium-ion battery used by NASA satellites. Batteries with various operating parameters (charging, discharging, and impedance) were tested at various temperatures. The dataset includes multiple attributes, including cycle, ambient temperature, datetime, capacity, voltage measured, current measured, temperature measured, actual load, voltage load, and time. The data includes 34 battery types, including B0055, B0028, B0030, B0018, and B0005. Table 1 presents a subset of the dataset.

2.2. Data preprocessing

The data preprocessing phase involves data filtering, SOH calculations, and the selection of battery data attributes. When data is filtered, the variety of battery with a fluctuating ratio of capacity to cycle curves is eliminated. The capacity and cycle curves of all varieties of batteries are examined, and the type of battery with a downward or good curve will be utilized in this study. The battery type data was filtered into nine distinct battery varieties, including B0005, B0006, B0007, B0018, B0025, B0026, B0027, B0028, and B0036.

During the preprocessing phase, the SoH calculation is also performed using (1). State of health (SoH) checks are performed on all battery types [17], [23].

$$SoH = \frac{C_C}{C_I} \times 100\% \tag{1}$$

C_C: the current cycle's maximum capacity
C_I: the first cycle's maximum capacity

The evaluation of battery data attributes is also performed during the preprocessing phase. The attributes cycle, ambient temperature, and datetime that are irrelevant to the li-ion battery SOH estimation process are removed. The data attributes utilised in this study are capacity, voltage measured, current measured, temperature measured, current load, voltage load, time, and SoH. The sample data after data preprocessing are displayed in Table 2.

Table 1. The dataset applied in this study

Cycle	Ambient temperature	Datetime	Capacity	Voltage measured	Current measured	Temperature measured	Current load	Voltage load	Time
1	24	2009-02-13 23:12:28	1.804685	4.166704	0.000899	26.507287	0.0002	4.181	29.500
1	24	2009-02-13 23:12:28	1.804685	3.930981	-1.998470	26.555082	1.9992	2.881	39.469
…	…	…	…	…	…	…	…	…	…
168	24	2008-05-27 20:45:42	1.325079	3.587336	0.001219	34.565580	0.0006	0.000	2810.640

Table 2. The dataset after data preprocessing

Capacity	Voltage measured	Current measured	Temperature measured	Current load	Voltage load	Time	SoH
1.804685	4.166704	0.000899	26.507287	0.0002	4.181	29.500	1.000000
1.804685	3.930981	-1.998470	26.555082	1.9992	2.881	39.469	0.946788
…	…	…	…	…	…	…	…
1.325079	3.587336	0.001219	34.565580	0.0006	0.000	2810.640	0.734243

2.3. Data modeling

This study estimates SoH using hybrid deep learning techniques, including standard deep learning-LSTM, Standard deep learning-BiLSTM, standard deep learning-SimpleRNN, CNN-LSTM, CNN-BiLSTM, and CNN-SimpleRNN. Hybrid deep learning methods are also compared to deep learning methods such as Standard Deep Learning, LSTM, BiLSTM, SimpleRNN, and CNN. Training battery data is conducted using battery data B0005, B0006, B0007, B0018, B0025, B0026, B0027, B0028, and B0036. The training data is differentiated by combining data for all battery types with training data for each battery type. In addition, data testing is conducted using B0055 battery data.

CNN-BiLSTM model is a hybrid deep learning technique that combines 1-D CNN with BiLSTM models. The CNN model is processed in parallel with the BiLSTM model. The CNN and BiLSTM models are combined to produce a model with concatenated features for estimating SoH. SoH calculations are performed during training and data testing so that predicted and actual SoH values can be compared.

The CNN model contains 1-dimensional convolutional which activates certain features of the data to produce a feature map, followed by rectified linear units (ReLU) which enable faster and more effective training. Furthermore, max pooling simplifies the output by performing nonlinear downsampling thereby reducing the number of parameters that the network needs to learn. The process continues with 1-dimensional convolutional+RELU and max pooling again. Then, flatten layer to convert the two-dimensional feature matrix into a vector. Finally, the fully connected layer (FCL) with the activation function is added with the number of neurons.

The BiLSTM model contains the BiLSTM layer and the dropout layer is repeated twice. The model is continued with dense_1 and dense_2 layers. Then, Flatten layer and FCL. The models are combined to produce concatenated features that combine features from the CNN and BiLSTM models. The model output can produce SoH estimates. The architecture of the CNN-BiLSTM model is shown in Figure 1.

2.4. Hyperparameter tuning

The hyperparameter optimization phase determines the parameters of the optimal experimental scenario. This study employs the parameters loss function, optimizer, batch_size, model activation, and epoch. Mean_squared_error is the loss function utilized in this study. Meanwhile, Adam is the optimizer used. Batch_Size is set to 50. The era utilized is 30. Then the employed activation model is tanh.

2.5. Evaluation

The research utilised four metrics to assess the effectiveness of the implemented procedure. This deep learning method is evaluated using mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE). In equations (2), (3), (4), and (5), the metrics are displayed [24], [25]. n is the amount of data that is measured or predicted. y_i is the actual SoH used in real terms, while $y_i^{\sim}$ is the predicted SoH produced by the model.

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

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y_i^{\sim})^2} \quad (3)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} | y_i - y_i^{\sim} | \quad (4)$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - y_i^{\sim}}{y_i} \right| \quad (5)$$

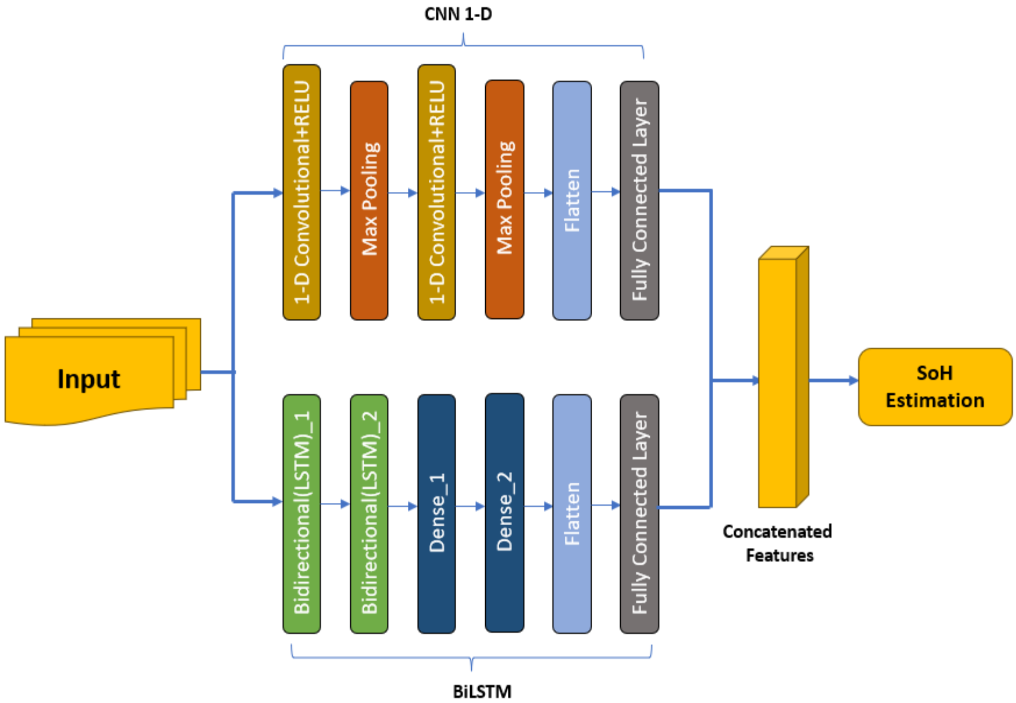


Figure 1. The CNN-BiLSTM architecture

3. RESULTS AND DISCUSSION

In this section, the results of the research are explained along with a comprehensive discussion. This section consists of data collection and results and discussion. The explanation of each method is as follows.

3.1. Data collection

In the NASA prognostics data repository, there are 301,710 records. There are a total of 251,073 records after preprocessing. The data are utilised as training data to construct a hybrid deep learning model for estimating the SoH of lithium-ion batteries. Using 22,662 records from the B0055 dataset to evaluate the deep learning model.

3.2. Result and discussion

This study uses eleven experimental scenarios for the estimation of the state of health of li-ion batteries. The experimental scenarios used are standard deep learning-LSTM, standard deep learning-BiLSTM, standard deep learning-SimpleRNN, CNN-LSTM, CNN-BiLSTM, CNN-SimpleRNN, standard deep learning, LSTM, BiLSTM, SimpleRNN, and CNN. The evaluation results of each method for estimating the SoH of lithium-ion batteries are displayed in Table 3.

The evaluation findings of this research, as shown in Table 3, indicate that CNN-BiLSTM outperformed other approaches. The CNN-BiLSTM approach yields the following values in the order of RMSE, MSE, MAE, and MAPE: 0.00916, 0.000084, 0.0048, and 0.00603. The hybrid deep learning method that obtained the next best results was standard deep learning-BiLSTM which obtained RMSE, MSE, MAE, and MAPE values respectively as follows: 0.00969, 0.000094, 0.00575, and 0.00724. The model that received the next best evaluation for a single deep learning model was BiLSTM with RMSE, MSE, MAE, and MAPE values respectively as follows 0.01075, 0.00011, 0.00649, and 0.00756.

Table 3. The evaluation of RMSE, MSE, MAE, and MAPE

Methods	RMSE	MSE	MAE	MAPE
Standard deep learning-LSTM	0.01094	0.00011	0.0058	0.00771
Standard deep learning-BiLSTM	0.00969	0.000094	0.00575	0.00724
Standard deep learning-SimpleRNN	0.01293	0.00016	0.00665	0.00814
CNN-LSTM	0.0168	0.00028	0.01013	0.01399
CNN-BiLSTM	**0.00916**	**0.000084**	**0.0048**	**0.00603**
CNN-SimpleRNN	0.01471	0.00021	0.00756	0.00902
Standard deep learning	0.04249	0.0018	0.02995	0.03824
BiLSTM	0.01075	0.00011	0.00649	0.00756
LSTM	0.01483	0.00022	0.01085	0.01264
SimpleRNN	0.01311	0.00017	0.00758	0.0092
CNN	0.02514	0.00063	0.01584	0.01928

This research also evaluates the performance of each battery type to estimate the State of Health of li-ion batteries. The following battery types are utilized: B0005, B0006, B0007, B0018, B0025, B0026, B0027, B0028, and B0036. Each type of battery is evaluated using standard deep learning, LSTM, BiLSTM, SimpleRNN, and CNN. Table 4 displays the evaluation results for RMSE, MSE, MAE, and MAPE for each type of battery used to estimate SoH.

Table 4 of the evaluation results for this study revealed that BiLSTM consistently produced the best results when compared to standard deep learning, LSTM, SimpleRNN, and CNN for each battery type. The B0025 battery achieved the greatest evaluation value with RMSE, MSE, MAE, and MAPE values of 0.00059, 3.4871, 0.00047, and 0.00048, respectively. Then, the model with the second-best evaluation results for each type of battery data is the SimpleRNN model.

This study illustrates the comparison curve between SoH and SoH predictions for every cycle. SoH that is used is SoH data from battery B0055, while SoH that is predicted is SoH prediction result from training data. The comparison of SoH and SoH predictions is depicted in Figure 2 (see in appendix). SoH is represented by the blue line, and predicted SoH is represented by the orange line.

Figure 2 shows that CNN-BiLSTM has a reasonably accurate model prediction and is near to the SoH value when compared to other methods. Figure 2 consists of subfigures including Figure 2(a) standard deep learning-LSTM, Figure 2(b) standard deep learning-BiLSTM, Figure 2(c) standard deep learning-SimpleRNN, Figure 2(d) CNN-LSTM, Figure 2(e) CNN-BiLSTM, Figure 2(f) CNN-SimpleRNN, Figure 2(g) standard deep learning, Figure 2(h) LSTM, Figure 2(i) BiLSTM, Figure 2(j) SimpleRNN, and Figure 2(k) CNN. CNN-BiLSTM provides model predictions within a range near or close to actual SoH values, resulting in superior performance in terms of prediction. Furthermore, CNN-BiLSTM can generalize well from training data to random data. CNN-BiLSTM has a low error rate when predicting SoH values. CNN-BiLSTM can effectively apply significant patterns extracted from training data to new data.

Figure 2 illustrates that compared to other approaches, the standard deep learning model accurately forecasts real SoH values throughout a broad spectrum. Conventional deep learning methods provide less precise model predictions for predicting SoH values. The model is influenced by bias in the training data, leading it to routinely forecast SoH values that are too high, resulting in a substantial disparity between the actual and anticipated SoH. The significant disparities across SoH curves might arise from measurement mistakes or flaws during the calculation of the precise SoH value. Should the data used for model training be inaccurate, it is likely that the model's predictions will also be imprecise.

CNN-BiLSTM is the optimal model for estimating SoH in lithium-ion batteries, according to this study. This technique is preferable to other hybrid and deep learning techniques. This is due to the fact that the combination of CNN and BiLSTM models can produce optimal model performance, allowing for better state of health prediction compared to other models. CNN's model excels at extracting hierarchical features from data in order to identify patterns that are difficult to recognise in numerical data. In contrast, BiLSTM is able to capture temporal patterns in data sequences. By combining CNN and BiLSTM, models are able to extract vital information, resulting in more robust representations of features. In addition, model CNN-BiLSTM can help reduce overfitting. CNN has a propensity to generate a large number of features, and

BiLSTM can help control the complexity of the model by utilizing contextual information from both data input directions. This can reduce the risk of overfitting that can occur with deep learning models. Utilizing the strengths of each architecture makes the combination of the CNN and BiLSTM models more advantageous than other models.

Table 4. The evaluation of RMSE, MSE, MAE, and MAPE for each battery type

Methods	RMSE	MSE	MAE	MAPE
Battery B0005				
Standard deep learning	0.05273	0.00278	0.031307	0.037176
BiLSTM	**0.00492**	**2.42811**	**0.00407**	**0.00484**
LSTM	0.04317	0.00186	0.03761	0.04714
SimpleRNN	0.01277	0.00016	0.01018	0.01203
CNN	0.05279	0.00278	0.03122	0.03697
Battery B0006				
Standard deep learning	0.07394	0.005468	0.0432	0.05756
BiLSTM	**0.00270**	**7.3333**	**0.00215**	**0.00284**
LSTM	0.01328	0.00017	0.00901	0.01094
SimpleRNN	0.00557	3.10398	0.00413	0.00558
CNN	0.07145	0.00510	0.04021	0.05311
Battery B0007				
Standard Deep Learning	0.01601	0.00025	0.00903	0.01063
BiLSTM	**0.00412**	**1.70461**	**0.00372**	**0.00425**
LSTM	0.01727	0.0002	0.01233	0.01325
SimpleRNN	0.006872	4.72300	0.00492	0.00576
CNN	0.01488	0.00022	0.00761	0.00890
Battery B0018				
Standard Deep Learning	0.02497	0.00062	0.01443	0.01701
BiLSTM	**0.00707**	**5.00178**	**0.00592**	**0.00693**
LSTM	0.00803	6.46041	0.00541	0.00669
SimpleRNN	0.02302	0.00053	0.00958	0.01146
CNN	0.02823	0.00079	0.01776	0.02113
Battery B0025				
Standard deep learning	0.00461	2.12995	0.00390	0.00397
BiLSTM	**0.00059**	**3.48716**	**0.00047**	**0.00048**
LSTM	0.00570	3.26040	0.00513	0.00524
SimpleRNN	0.00089	8.00543	0.00058	0.00059
CNN	0.00457	2.08875	0.00410	0.00418
Battery B0026				
Standard deep learning	0.00871	7.59889	0.00418	0.00472
BiLSTM	**0.00228**	**5.20353**	**0.00197**	**0.00207**
LSTM	0.00242	5.86066	0.00170	0.00174
SimpleRNN	0.00512	2.62785	0.00491	0.00509
CNN	0.00277	7.71735	0.00219	0.00228
Battery B0027				
Standard deep learning	0.00295	8.74244	0.00228	0.00231
BiLSTM	**0.00075**	**5.72049**	**0.00057**	**0.00057**
LSTM	0.00721	5.20097	0.00663	0.00671
SimpleRNN	0.00367	1.35289	0.00342	0.00346
CNN	0.00315	9.97627	0.00265	0.00267
Battery B0028				
Standard deep learning	0.00352	1.24535	0.00278	0.00285
BiLSTM	**0.00146**	**2.14991**	**0.00095**	**0.00098**
LSTM	0.00464	2.15431	0.00398	0.00407
SimpleRNN	0.00158	2.51209	0.00137	0.00139
CNN	0.00244	5.99046	0.00189	0.00193
Battery B0036				
Standard deep learning	0.01118	0.00012	0.00387	0.00556
BiLSTM	**0.00273**	**7.47552**	**0.00176**	**0.00252**
LSTM	0.00652	4.25574	0.00455	0.00661
SimpleRNN	0.00328	1.07758	0.00213	0.00298
CNN	0.01065	0.00011	0.00843	0.01216

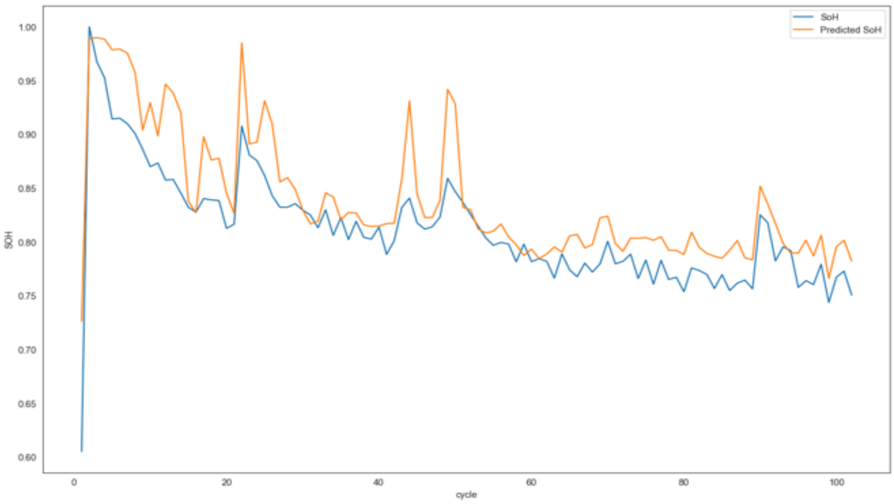
Evaluation of a single deep learning model yields a BiLSTM model that is superior to other models. BiLSTM is a recurrence model capable of capturing temporal relationships in data. BiLSTM enables the model to see the context before and after a given time, which is crucial for identifying trends and patterns for li-ion battery SoH estimation. BiLSTM is capable of identifying Li-ion battery characteristics such as degradation over time and variations in response during charge and discharge cycles. BiLSTM is well-suited to this type of task due to its capacity to recall past information and use it to make predictions about the future.

4. CONCLUSION

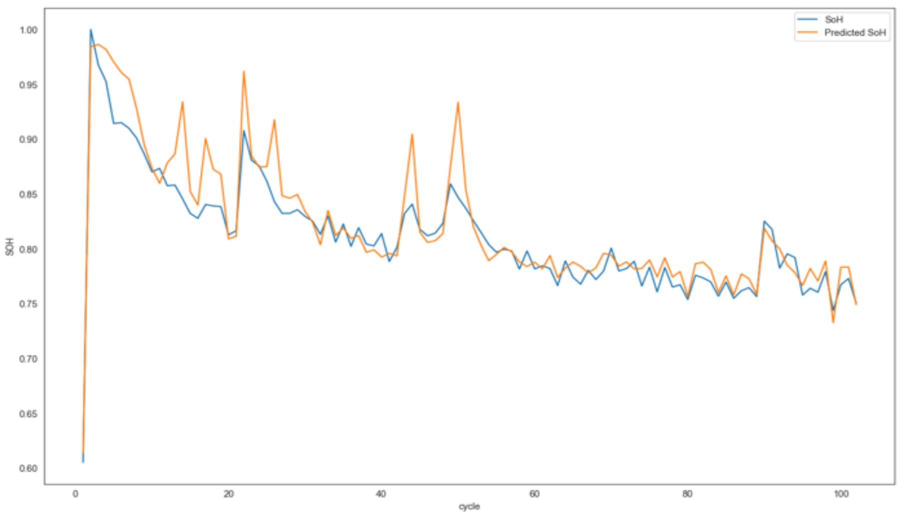
The study successfully estimated the SoH of lithium-ion batteries using hybrid deep learning methods. The hybrid deep learning methods used in this study are standard deep learning-LSTM, standard deep learning-BiLSTM, standard deep learning-SimpleRNN, CNN-LSTM, CNN-BiLSTM, and CNN-SimpleRNN. This research compares hybrid deep learning methods with single deep learning models such as standard deep learning, LSTM, BiLSTM, SimpleRNN, and CNN. CNN-BiLSTM has the best results compared to other methods. The CNN-BiLSTM method obtains RMSE, MSE, MAE, and MAPE in sequence of 0.00916, 0.000084, 0.0048, and 0.00603. The model that received the next best evaluation for a single deep learning model was BiLSTM with RMSE, MSE, MAE, and MAPE values respectively as follows 0.01075, 0.00011, 0.00649, and 0.00756. This suggests that the CNN-BiLSTM has the ability to estimate the best Li-ion battery SoH compared to other methods.

Future research can combine CNN transfer learning models such as Resnet50, VGG19, InceptionV3 to predict State-of-Health on li-ion batteries. Ensemble transfer learning CNN can be combined with other models such as BiLSTM or LSTM to produce better performance because it combines the advantages of these methods. Future research can also estimate the RUL of li-ion batteries so that the results obtained are more comprehensive than only estimating SoH.

APPENDIX

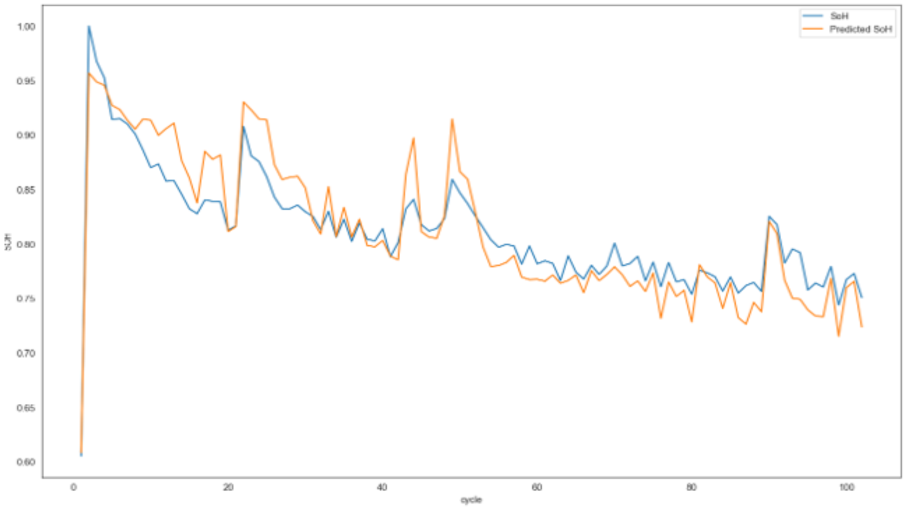


(a)

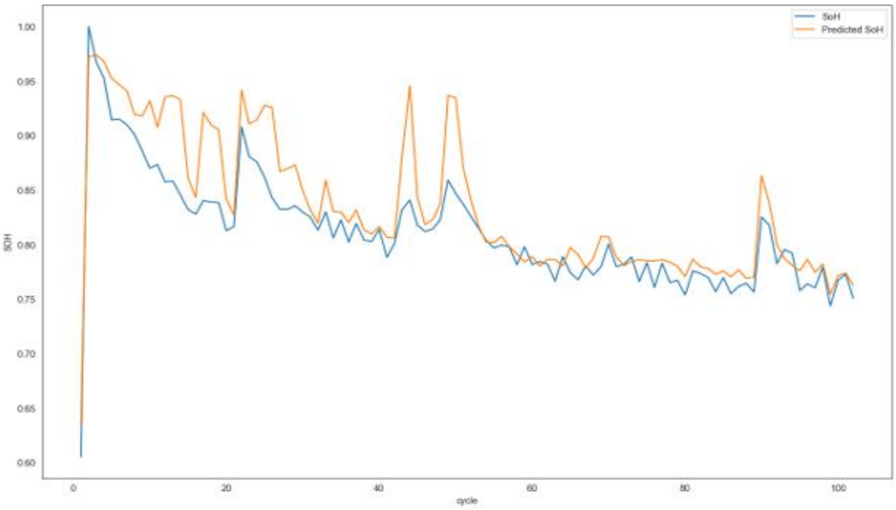


(b)

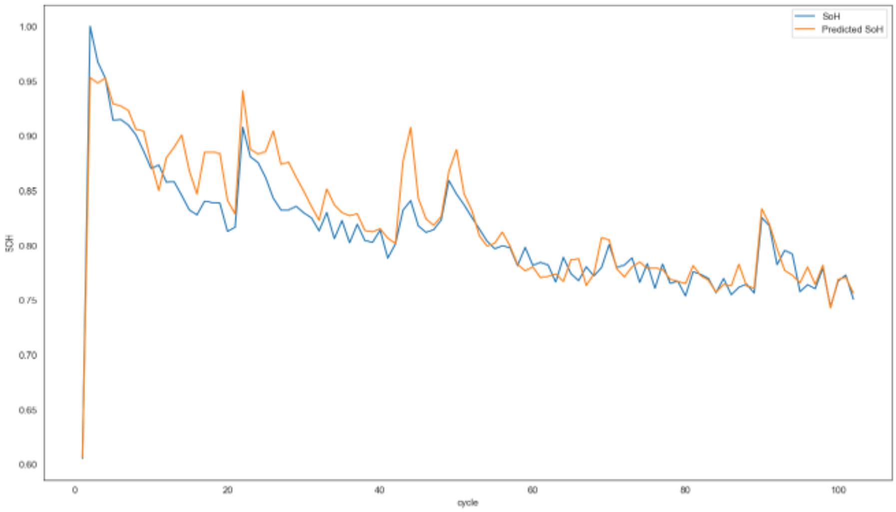
Figure 2. Curve of comparison between SoH and predicted SoH (a) standard deep learning-LSTM and (b) standard deep learning-BiLSTM



(c)

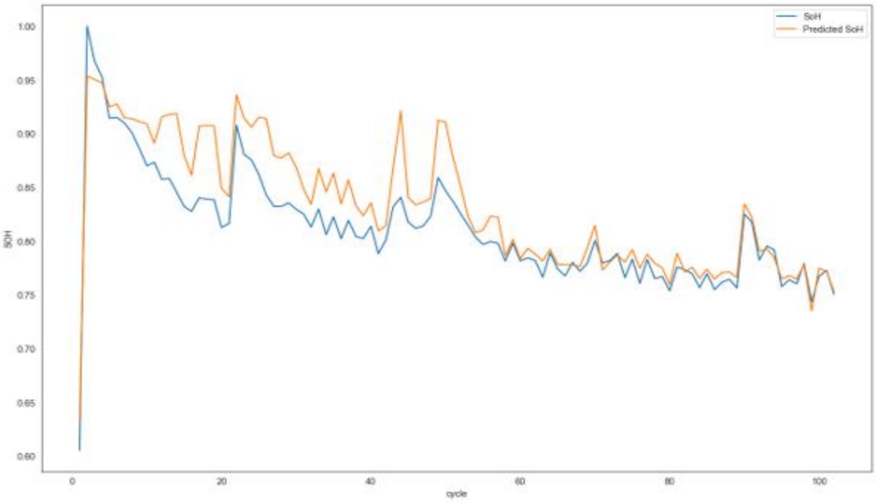


(d)

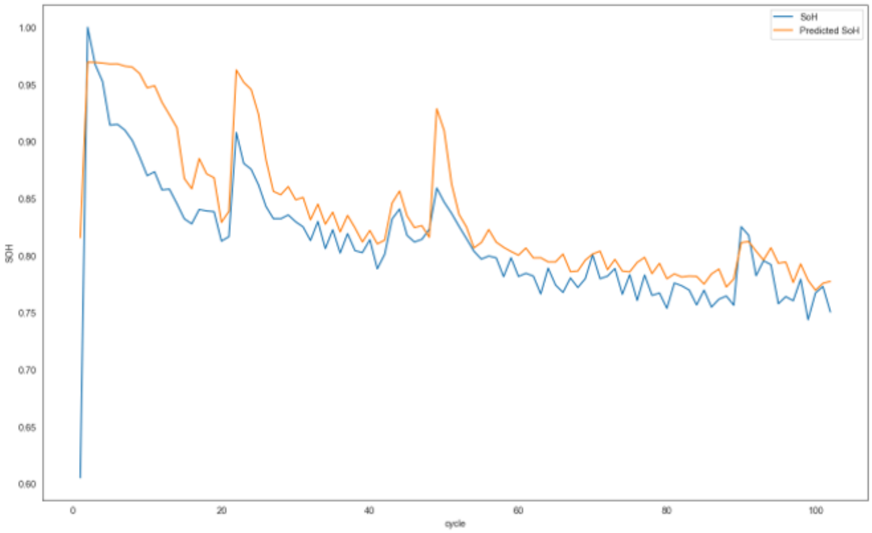


(e)

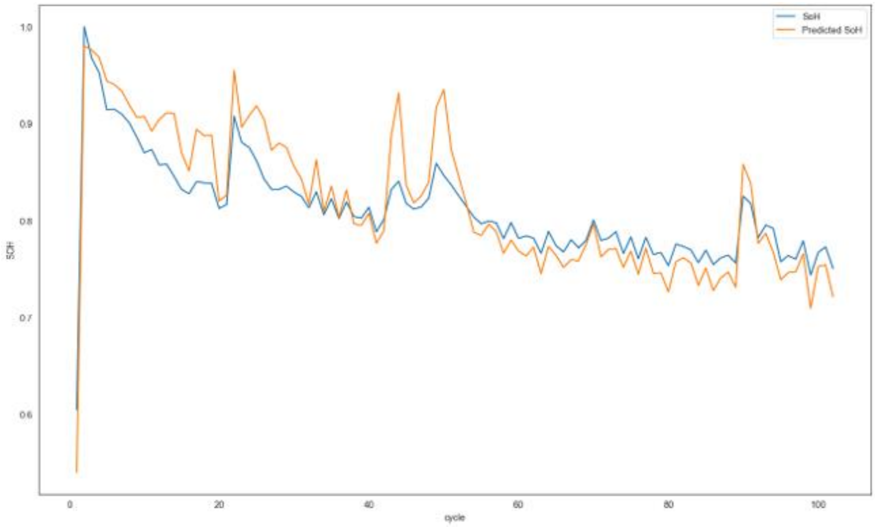
Figure 2. Curve of comparison between SoH and predicted SoH (c) standard deep learning-SimpleRNN, (d) CNN-LSTM, and (e) CNN-BiLSTM



(f)

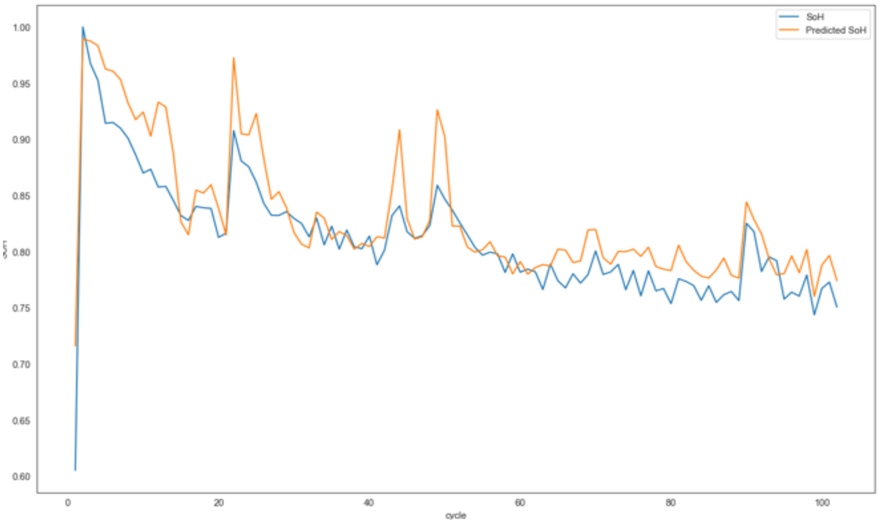


(g)

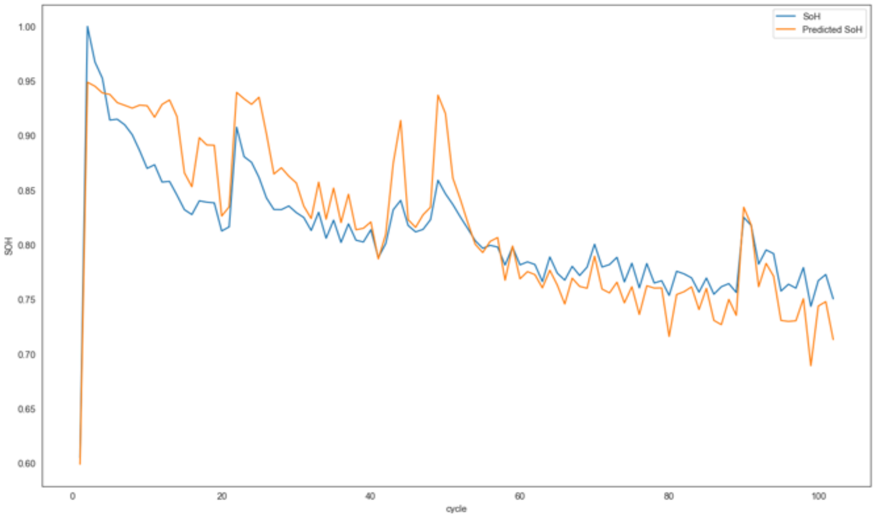


(h)

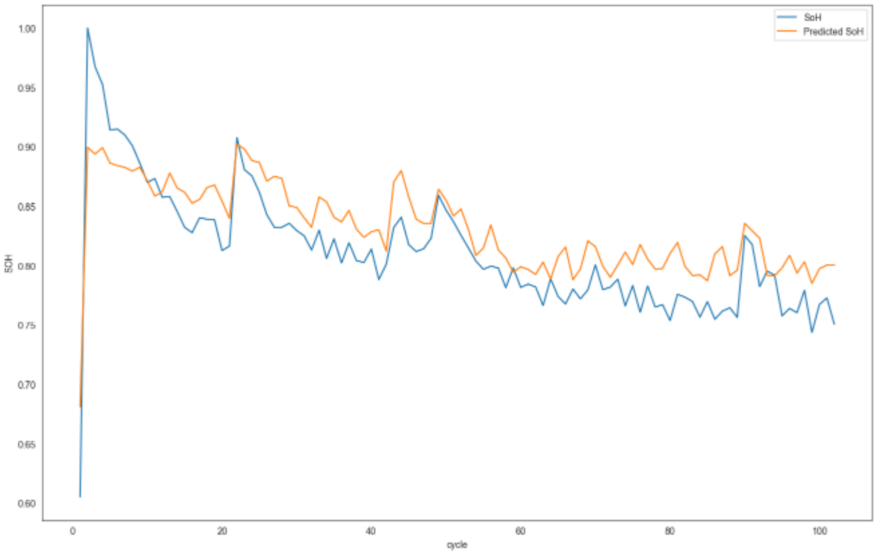
Figure 2. Curve of comparison between SoH and predicted SoH: (f) CNN-SimpleRNN, (g) standard deep learning, and (h) LSTM



(i)



(j)



(k)

Figure 2. Curve of comparison between SoH and predicted SoH: (i) BiLSTM, (j) SimpleRNN, and (k) CNN

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