State of Health Estimation of Lithium-ion Batteries Using Convolutional Neural Network with Impedance Nyquist Plots

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Abstract: In order to maintain the Li-ion batteries in a safe operating state and to optimize their performance, a precise estimation of the state of health (SOH), which indicates the degradation level of the Li-ion batteries, has to be taken into consideration urgently. In this paper, we present a regression machine learning framework that combines a convolutional neural network (CNN) with the Nyquist plot of Electrochemical Impedance Spectroscopy (EIS) as features to estimate the SOH of Li-ion batteries with a considerable improvement in the accuracy of SOH estimation. The results indicate that the Nyquist plot based on EIS features provides more detailed information regarding battery aging than simple impedance values due to its ability to reflect impedance change over time. Furthermore, convolutional layers in the CNN model were more effective in extracting different levels of features and characterizing the degradation patterns of Li-ion batteries from EIS measurement data than using simple impedance values with a DNN model, as well as other traditional machine learning methods, such as Gaussian process regression (GPR) and support vector machine (SVM).

1 INTRODUCTION

The use of lithium-ion (Li-ion) batteries has gained considerable attention as one of the most promising means of reducing net carbon dioxide emissions for a wide range of industrial applications. During the use of Li-ion batteries, degradation of capacity occurs as an irreversible process, resulting in diminished performance and increased safety operation concerns. State of health (SOH) is determined as the ratio of the current maximum capacity of Li-ion batteries to the maximum capacity when the battery is fresh, which is the degradation indicator of Li-ion batteries that reflects the current health condition of the batteries compared to its initial health condition. SOH estimation is vital not only for maintaining the optimal performance of electric vehicles (EVs) but also for performing health assessments on Li-ion batteries, which provides vital information regarding battery maintenance and replacement (Rauf et al., 2022). Unlike voltage, current, and temperature, the SOH of Li-ion batteries cannot be measured directly with gauges in a battery management system (BMS). The coulomb counting (Ng et al., 2009) as a direct capacity measurement has been widely used in a laboratory environment to measure the capacity of Li-ion batteries, in which a complete discharge and charge cycle is necessary at each measurement. Due to the fact that frequent discharging and charging is a time-consuming process that can accelerate the aging of Li-ion batteries, it is impractical to implement the coulomb counting in real-life applications where a real-time estimation is needed. Thus, designing robust and reliable battery management systems that estimate SOH accurately remains a challenge.

Recent advances in artificial intelligence (AI) and the availability of large Li-ion battery datasets have resulted in the development of a wide range of data-driven methods that are capable of estimating the SOH of Li-ion batteries accurately, in which a continuous capacity estimation task has been converted into a regression machine learning problem. The quality of the Li-ion battery dataset has a great deal of significance since data-driven models are based upon measurable battery data in order to provide a robust estimation of the battery capacity without delving deeply into electrochemical phenomena inside the battery. As a result, it remains difficult to select a suitable supervised machine learning model with effective feature sets for accurate battery SOH estimation. In recent years, extensive research has been conducted on extracting degradation patterns from Li-ion batteries and mapping their relationship with capacity using voltage, current, and temperature from charg-

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ing curves. In practice, however, the charging patterns of users vary, which results in uncertainty in the charging data collected. Thus, in order to overcome the limitations of adopting multi-channel battery features, including battery voltage, current, and temperature from charging curves, this paper proposes a machine learning framework, in which Electrochemical Impedance Spectroscopy (EIS) data from impedance curves are combined with a convolutional neural network (CNN) to estimate the SOH of Li-ion batteries.

The novelty and contributions of this paper are summarized as follows.

- EIS features have been demonstrated in previous work (Li et al., 2021) that they can be efficiently utilized in Li-ion battery State of Charge (SOC) estimation with better accuracy than a multi-channel feature set using a deep neural network. Now that SOC estimation has been extended to SOH estimation, and a promising level of accuracy has been observed for SOH estimation using the EIS feature set.
- To the best of our knowledge, this is the first time that the Nyquist plot of EIS features has been integrated with the CNN model as features in order to estimate the SOH of Li-ion batteries. According to the implementation results, Nyquist plots of impedance provide more comprehensive information on battery aging than simple impedance values in terms of describing nonlinear and complex degradation processes of lithium-ion batteries, resulting in substantial improvements in SOH prediction accuracy of Li-ion batteries.
- This study demonstrated that convolutional layers in the CNN model were more effective in extracting different levels of features from EIS Nyquist plots and analyzing degradation patterns of Li-ion batteries than simple impedance values with a deep neural network (DNN), as well as other conventional machine learning techniques, such as Gaussian Process Regression (GPR) and support vector machine (SVM).

The remainder of the paper is organized as follows: Section II summarizes the recent state-of-art research work regarding the SOH estimation of Li-ion batteries. Section III describes the utilized EIS dataset and the proposed machine learning framework. Section IV highlights the results and comparisons obtained from the employed models with the EIS feature set. Finally, the conclusion is drawn in Section V.

2 RELATED WORK

This section summarizes related published work regarding the SOH estimation of Li-ion batteries. In spite of the challenge of designing a BMS that is capable of estimating SOH accurately, it is vital to ensure the reliability and safety of Li-ion batteries for various applications. Therefore, the development of novel methods for the states estimation of Li-ion batteries has received significant attention in recent years. Generally, the majority of research studies conducted so far can be divided into two broad categories, model-based models and data-driven models.

The model-based methods are highly dependent on the domain knowledge of multi-physics phenomena of Li-ion batteries, including electrochemistry and aging characteristics. The Kalman filter has been proposed in (Saxena et al., 2019) for the estimation of SOC and SOH of Li-ion batteries. In (Daigle et al., 2016), An Equivalent Circuit Model (ECM) was developed by Daigle and Kulkarni to predict battery capacity when batteries were discharged. An extended Kalman filter (EKF) and an enhanced self-correcting equivalent circuit model were used by Plett (Plett et al., 2004) to achieve an online capacity estimation of the Li-ion battery cell. According to (Lin et al., 2017), two sliding mode observers can be used to determine the SOC and SOH of Li-ion batteries coupled with a reduced order electrochemical model (EM). Because EMs contain a large number of partial differential equations, their solution requires a significant amount of computational power.

The use of model-based methods involves the development of complex mathematical models that are designed to account for the long-term dependencies of battery degradation and to describe the degradation process. However, the lack of domain knowledge regarding model construction precludes the use of these methods in real-world applications since it is infeasible to identify all the hidden complex and highly nonlinear degradation characteristics. In contrast, data-driven models utilize machine learning techniques to provide an accurate estimation of the SOH of Li-ion batteries, thereby overcoming the lack of generality in model-based approaches for different types of batteries. As a consequence of the advantages of using machine learning techniques, data-driven methods rely solely on experimental data collected from the battery without taking into account battery aging mechanisms and internal electrochemical reactions.

In (Choi et al., 2019), as a result of exploiting and applying multi-channel charging profiles of the battery voltage, current, and surface temperature to deep learning models, numerical results indicate that the proposed multi-channel method delivers up to 58% mean absolute percentage error (MAPE) improvement by deploying various neural networks in comparison with the use of only voltage charging profiles. The feed-forward neural network (FFNN) has been deployed in (Chaoui et al., 2017) to estimate the SOH of Li-ion batteries by using input features, including battery terminal voltage, current, and ambient temperature from charging curves, which enables the neural network to extract the dynamic characteristics from Li-ion batteries and map them to the capacity. To estimate the SOH of Li-ion batteries, a gate recurrent unit-convolutional neural network (GRU-CNN) was proposed in (Fan et al., 2020), which can extract the shared information and time dependencies from the charging curve and limit the maximum prediction error to 4.3%. The authors in (Yang et al., 2022) have utilized the battery data from charging/discharging curves and fed them into various CNN-based SOH estimation models, indicating the effectiveness of the proposed models in predicting the SOH of Li-ion batteries.

The data-driven methods mentioned above all rely heavily on the charging curve data, but the charging patterns of users are difficult to predict, resulting in randomness in the battery charging data. As an alternative to using battery voltage, current, and temperature from charging curves, EIS has gained increased interest from researchers in recent years for its non-destructive nature and capability to analyze the impedance spectrum of batteries.

It has been demonstrated in (Li et al., 2021) that the EIS feature set was more effective and efficient in predicting Li-ion battery capacity than battery voltage, current, and temperature from charging curves. Incorporating cycle numbers with EIS features in (Li et al., 2022) improved the SOH estimation accuracy by up to 50% compared to those relying solely on EIS features. The authors in (Kim et al., 2022) propose an unsupervised machine learning model called EIS-based InfoGAN (EISGAN), which extracts variables that can precisely formulate battery degradation from the EIS feature set with low-frequency fluctuations. An acceptable level of prediction accuracy can be achieved with a mean absolute error (MAE) of 0.71 and a root mean square error (RMSE) of 0.91, respectively, for testing on a single cell. Moreover, a CNN model has been deployed with EIS measurement data to estimate the SOH of Li-ion batteries in (Pradyumna et al., 2022), where the maximum estimation error was found to be 0.57 (% capacity) and the RMSE was found to be 0.233 (% capacity).

Despite the high dimensionality of EIS features, it has been challenging to select the quantitative features that correlate with battery degradation when using EIS measurements to predict the SOH of lithium-ion batteries. Hence, a CNN model has been developed in this paper, in which the convolutional layer is employed to extract the most useful features from the input data automatically without omitting any critical characteristics of the battery data.

3 MATERIAL AND METHODOLOGY

This section discusses Zhang's EIS dataset (Zhang et al., 2020), one of the largest publicly available EIS datasets to date, as well as how EIS features were extracted and restructured in different ways to characterize battery degradation patterns. Also, a proposed machine learning framework will be described where the CNN and DNN models were deployed to extract the aging characteristics from EIS features to estimate the SOH of Li-ion batteries. The proposed machine learning framework in this work is presented in Figure 1.

3.1 Data Acquisition

Various non-linear mechanisms and complex decline trajectories are involved in the degradation of Li-ion batteries. In order to train a machine learning model that will accurately predict the SOH of Li-ion batteries, reliable battery aging data are essential.

In light of the difficulty of conducting battery aging experiments, researchers have evaluated their proposed prediction algorithms based on publicly available battery datasets. A comprehensive dataset of EIS measurements, as specified in (Zhang et al., 2021), was selected for this experiment, which was conducted by continuously charging and discharging 12 Eunicell LR2032 lithium-ion coin cells made of LiCoO2/graphite.

Battery internal impedance plays an important role in determining its operational voltage, rate capability, and efficiency, and can even have a significant impact on its practical capacity. In general, the measurement approach involves applying a sinusoidal current or voltage with a certain amplitude and frequency, and measuring the amplitude and phase shift of the output voltage or current (Li et al., 2020). Repeating this procedure for various frequencies, typically between kHz and MHZ, yields a characteristic impedance spectrum. More than 20,000 EIS spectra of 12 commercial Li-ion batteries have been collected in the EIS dataset (Zhang et al., 2021). The samples were cycled at different temperatures, specifically,

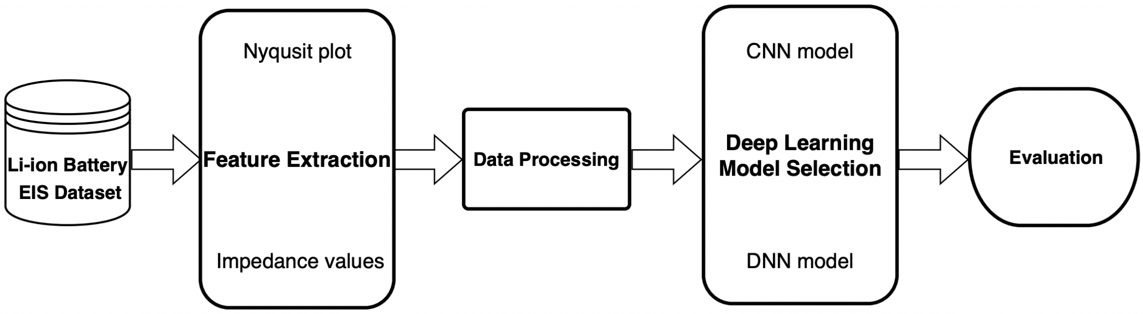

Figure 1: The proposed supervised machine learning framework.

eight cells were cycled at 25°C, two cells at 35°C, and the remaining cells were cycled at 45°C. EIS measurement data are collected spanning a frequency range from 0.02 HZ to 20 KHZ, in which 60 sample points were conducted at each charging/discharging cycle.

3.2 Feature Extraction

Due to the complexity and non-linearity of the Li-ion battery aging process, selecting the most significant patterns from the EIS feature set plays an important role in describing the degradation of Li-ion batteries. In this work, the Nyquist plot of EIS features has been extracted based on different cycle numbers of charging/discharging of Li-ion batteries, while simple impedance values also have been restructured to characterize the battery aging patterns.

3.2.1 Nyquist Plot

By varying the applied frequency in an EIS measurement, considerable information can be gathered. Nyquist plots have been commonly used to visualize the complex values of impedance values. A Nyquist plot at one sample point where the real part of the impedance is plotted against the imaginary part was presented in Figure 2, where each blue dot represents a complex value of the impedance, and 60 different blue dots were collected at each frequency point.

In order to visualize how the Nyquist plot can reflect the degradation of Li-ion batteries, several Nyquist plots with respect to various SOH of Li-ion batteries have been shown in Figure 3, where the plot curves of impedance shift as the result of battery aging.

3.2.2 Impedance Values

The EIS measurement data have been restructured in different ways to describe the aging patterns of Li-ion batteries. For various deep learning models, different data representations may be needed to take advantage

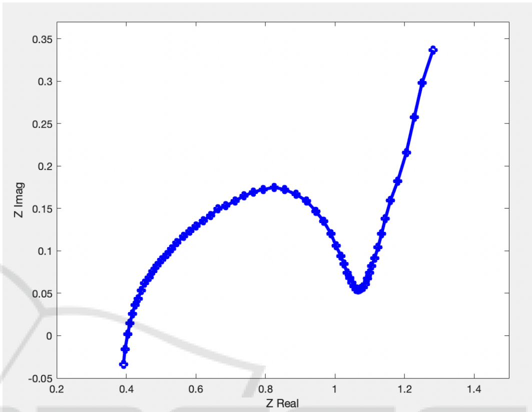

Figure 2: Nyquist plot of impedance at one sample point.

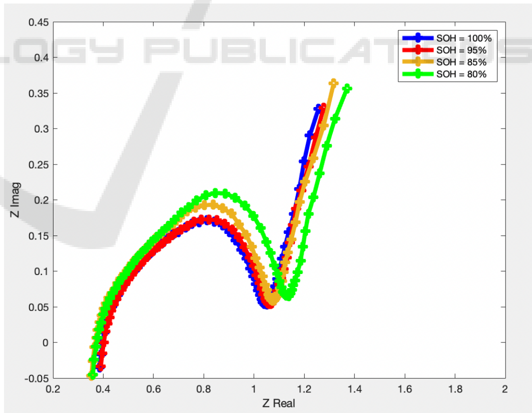

Figure 3: Nyquist plots of impedance at different SOH.

of each deep learning model. Instead of representing the EIS features of Li-ion batteries, another commonly adopted way to describe the data is to use a single column array to formulate the impedance values, where EIS measurement data are organized as a 120 x 1 array.

3.3 Data Processing

A data processing step is essential before feeding the input data into the machine learning model. In this step, EIS measurement data are normalized and restructured before being fed into a neural network model.

3.3.1 Data Normalization

Normalization of data refers to the process of reorganizing information in a database to reduce redundancy and enhance its efficiency by making all features on the same scale. The Min-Max function was used to normalize EIS measurement data in this study:

$$x_{n_{scaled}} = \frac{x_n - x_{min}}{x_{max} - x_{min}} \tag{1}$$

In this case, x_n represents each element in feature column n, and x_{min} and x_{max} are the minimum and maximum values for each feature column, respectively. Impedance value in each feature column will be scaled between 0 and 1 at the end of the normalization, which enables each feature in EIS measurement data of equal importance.

3.4 Model Selection

A CNN framework has been proposed to estimate the SOH of Li-ion batteries in this study, while a DNN model has also been deployed with the same EIS measurement data in order to compare the performance of the models.

3.4.1 Convolutional Neural Network

There has been considerable interest in using convolutional neural networks as a powerful tool for dealing with computer vision problems, where CNNs are used to classify and differentiate between various objects contained in an image. In this study, a CNN framework has been proposed and presented in Figure 4. There are 1657 Nyquist plots each with a size of (1657x420) that have been fed into the CNN model where two convolutional layers each with a max pooling layer after are followed by there fully connected dense layers to extract the aging patterns from the images and map the relationships to the capacity value of Li-ion batteries.

Typically a CNN model is composed of multiple layers with different functionalities, including input layer, convolutional layers, pooling layers, flatten layer, hidden layers, and output layer. The purpose of the Convolution Operation is to extract high-level features from the input image, such as edges. In CNN models, multiple convolutional layers are usually required since the architecture is designed to take into account high-level features as additional convolutional layers are added. Similar to the convolutional Layer, the Pooling layer is designed to reduce the spatial size of the convolved feature, which decreases the computation complexity and results in a more efficient model. Now that the input image has been converted into a form suitable for multi-level perceptrons, the image should be flattened into a column vector in order to feed it into a feed-forward neural network that employs backpropagation for each iteration of training. With the help of the optimization algorithm, the model is able to distinguish dominating and certain low-level features in images and classify them accordingly.

3.4.2 Deep Neural Networks

The DNN is one of the most promising deep learning techniques, particularly when a large amount of data is involved, which can be used to learn the dynamics and nonlinear degradation patterns of Li-ion batteries for a regression SOH estimation task. Generally, a DNN model refers to a simple feed-forward neural network, which consists of multiple layers, including the input layer, hidden layers, and output layer. The selection of the number of layers and the number of neurons in each specific layer make a significant difference in the prediction performance of models, where the tuning of hyperparameters in a DNN model should be taken into consideration carefully. Previous works (Li et al., 2022), (Chemali et al., 2018) have provided an insight into what combination of the hyperparameters should be selected in the DNN model with the comparable input data size to estimate the SOH of Li-ion batteries due to the complexity and time-consuming nature of hyperparameters optimization. The input data in the input layer is composed of 120 neurons, are fed sequentially to two hidden layers with 64 and 32 neurons in each one, respectively. ReLU function was assigned as the activation function in both hidden layers and the output layer to formulate the nonlinear aging process of Li-ion batteries. Adam algorithm was utilized to optimize the loss function computed by mean squared error (MSE) in each iteration to adjust the weights and bias of the DNN model. Also, a dropout layer with a dropout rate of 0.1 was added after the hidden layers to avoid the potential overfitting during the training phase. The hyperparameters defined in the DNN model have been presented in Table I.

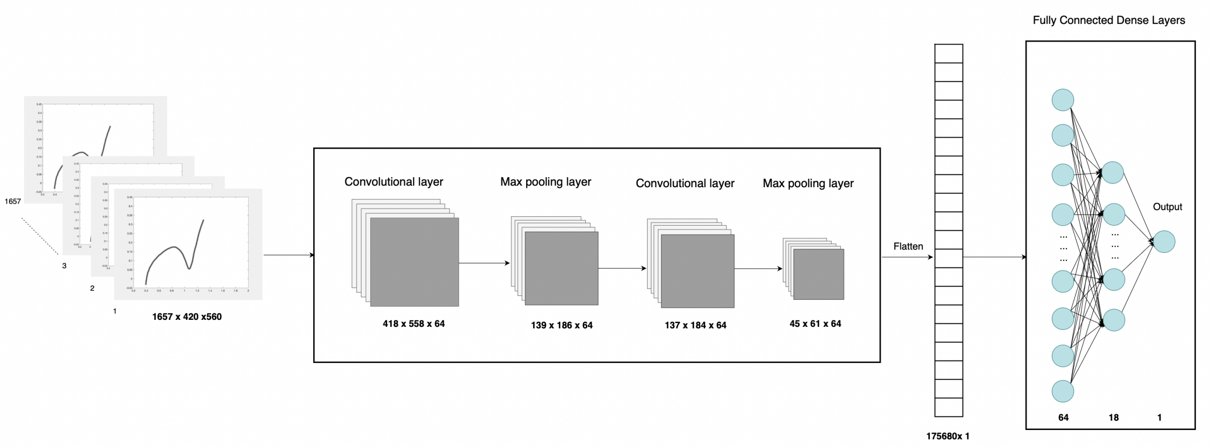

Figure 4: The proposed CNN framework.

Table 1: DNN Hyperparameters.

Hyperparameter	Selection Options
Input size	120 x 1
Number of hidden layers	2
Number of neurons in the first hidden layer	64
Number of neurons in the second hidden layer	32
Output size	1
Optimization algorithm	Adam
Dropout rate	0.1
Activation function for hidden & output layers	ReLU
Loss function	Mean squared error
Batch size	32

3.5 Evaluation

Mean square error and mean absolute error are two widely used evaluation metrics for regression machine learning problems. And they were utilized to evaluate the performance of employed CNN and DNN models in this study.

3.5.1 Mean Squared Error

Mean square error is defined as the mean of the square of the difference between real and predicted values in statistics. In this case, it is computed by taking the mean of the square of the difference between the true capacity $y_{i_{true}}$ and the predicted one $y_{i_{predicted}}$ as shown in:

$$MSE = \sum_{i}^{n} \frac{(y_{i_{predicted}} - y_{i_{true}})^2}{n} \tag{2}$$

The smaller value of MSE indicates better SOH prediction accuracy of Li-ion batteries.

3.5.2 Mean Absolute Error

Mean Absolute Error represents an average value of the sum of the absolute difference between actual and predicted results. In this case, it is computed by taking the mean of the sum of the absolute value of the difference between predicted capacity $y_{i_{predicted}}$ and actual capacity $y_{i_{true}}$, which is shown in:

$$MAE = \sum_{i}^{n} \frac{|y_{i_{predicted}} - y_{i_{true}}|}{n} \tag{3}$$

The smaller MAE value indicates a better prediction result.

4 RESULTS AND DISCUSSION

In this work, two different data representations are derived from normalized EIS measurement data, the Nyquist plot of impedance in binary images and 120 x 1 single-column vectors, respectively, in order to formulate the degradation mechanism of Li-ion batteries through CNN and DNN models. Input data have been divided into 90% training data and 10% testing data to assess the generalization ability of trained models. In addition, 10% of the training set was split into a validation set to prevent the models from overfitting during the training phase. For the statistical analysis and evaluation of the SOH prediction of Li-ion batteries, CNN and DNN models were implemented in Python based on TensorFlow.

The deployed CNN model extracted and learned the changing patterns of the curves of the impedance plot to predict the SOH of Li-ion batteries, while the DNN model can only learn the features from the single-column impedance array due to the limitation of its simple structure. The prediction results indicate both the DNN and CNN models were capable of characterizing the dynamic and nonlinear aging patterns of Li-ion batteries from EIS measurement data. Moreover, because of that, convolutional layers prior to dense layers that are fully connected can effectively extract aging patterns from Nyquist plots, and Nyquist plots contain much more detailed information regarding the battery degradation process than simple impedance values, which resulted in a significant accuracy improvement of the SOH prediction in CNN model as compared to the DNN model. As an additional step, simple impedance values were fed into traditional machine learning methods, including SVM and GPR models. It is evident from the results that the CNN model with Nyquist plots as features achieved an improved SOH prediction accuracy with MSE and MAE errors of 0.0458 and 0.1292, respectively, outperforming other methods presented in Figure 5.

As an alternative to the impedance plot, a single-column array is used to represent the impedance value, which is composed of a real part of the impedance value followed by a imaginary part of it. The Nyquist plot shows the actual fluctuation of impedance, while the single-column impedance array only reflects the impedance values of the Li-ion batteries. Accordingly, the prediction results on the Nyquist plot shows an considerable accuracy improvement compared to the single-column impedance array in SOH prediction, which explains why the Nyquist plot is better suited to characterizing Li-ion battery degradation patterns than the single-column impedance array by using the CNN model.

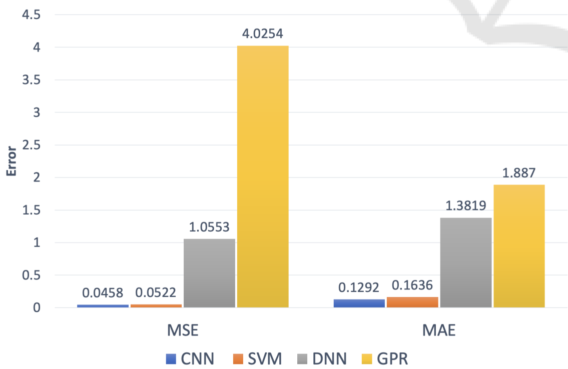

Figure 5: Performance comparison between CNN model with Nyquist Plot and DNN, SVM and GPR models with simple impedance values.

5 CONCLUSIONS

This study proposed a CNN framework for estimating the SOH of Li-ion batteries using deep learning techniques. Firstly the EIS feature set has been extracted and normalized using the Min-Max function from the raw EIS measurement dataset. Next, the EIS feature set was restructured into two different forms, the Nyquist plot and simple impedance values, in order to to be fed into different neural networks and traditional machine learning models. Based on simulation results on one of the largest publicly available EIS datasets, the EIS features set in the Nyquist plot form contains more detailed information than simple impedance values regarding the battery aging process owing to its ability to reflect the impedance change at various SOH stages. Furthermore, the results demonstrated that the content that reflects the fluctuation of impedance in the Nyquist plots makes a difference in the SOH prediction compared to single-column impedance array. Additionally, the CNN model with two convolutional layers, which incorporates Nyquist plots as features, significantly improved SOH prediction accuracy when compared to the DNN model and other machine learning models that rely solely on simple impedance values. Future studies should take into account more various EIS data representations and evaluation metrics in order to overcome critical scenarios in the operations of EVs, and ensure the reliability and robustness of the SOH prediction of Li-ion batteries in real world.

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