International Journal of Advanced Culture Technology Vol.11 No.3 310-314 (2023)
DOI https://doi.org/10.17703/IJACT.2023.11.3.310

IJACT 23-9-40

Performance Comparison Analysis of Artificial Intelligence Models for Estimating Remaining Capacity of Lithium-Ion Batteries

Kyu-Ha Kim [1], Byeong-Soo Jung [2], Sang-Hyun Lee [3]

[1,3] *Associate Prof., Dept. Computer Engineering, Honam University, Korea*
[2] *Prof., Dept. IT&Management, Nambu University, Korea*

{kim9659, leesang64}@honam.ac.kr, bsjung@nambu.ac.kr

Abstract

The purpose of this study is to predict the remaining capacity of lithium-ion batteries and evaluate their performance using five artificial intelligence models, including linear regression analysis, decision tree, random forest, neural network, and ensemble model. We is in the study, measured Excel data from the CS2 lithium-ion battery was used, and the prediction accuracy of the model was measured using evaluation indicators such as mean square error, mean absolute error, coefficient of determination, and root mean square error. As a result of this study, the Root Mean Square Error(RMSE) of the linear regression model was 0.045, the decision tree model was 0.038, the random forest model was 0.034, the neural network model was 0.032, and the ensemble model was 0.030. The ensemble model had the best prediction performance, with the neural network model taking second place. The decision tree model and random forest model also performed quite well, and the linear regression model showed poor prediction performance compared to other models. Therefore, through this study, ensemble models and neural network models are most suitable for predicting the remaining capacity of lithium-ion batteries, and decision tree and random forest models also showed good performance. Linear regression models showed relatively poor predictive performance. Therefore, it was concluded that it is appropriate to prioritize ensemble models and neural network models in order to improve the efficiency of battery management and energy systems.

Keywords: *Lithium-ion Battery, Remaining Capacity, Linear Regression Model, Decision Tree Model, Random Forest Model, Neural Network Model, Ensemble Model.*

1. INTRODUCTION

Lithium-ion batteries are widely used in electric vehicles, energy storage systems (ESS), smartphones, tablets, laptops, and various portable devices due to their advantages of high-power output and lightweight [1].

The prediction of battery failures is considered a crucial issue, and NASA is conducting research on battery failure prediction and health management using big data and machine learning. This enables the prevention of accidents or failures and minimizes operational disruptions. Recently, various models utilizing artificial neural networks have been developed, leading to advancements in fault prediction technology [2]. The field of artificial intelligence is continuously evolving, with the development and improvement of new models and algorithms [3]. To evaluate the performance of representative artificial intelligence models for estimating the

Manuscript received: July 17, 2023 / revised: August 10, 2023 / accepted: August 30, 2023
Corresponding Author: leesang64@honam.ac.kr
Tel : +82-62-940-5285
Associate Professor, Dept. of Computer Engineering, Honam University, Korea

residual capacity of lithium-ion batteries, various metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared Score, and RMSE are employed [3]. These metrics measure the differences between the predicted values and the actual values, allowing for the assessment of prediction accuracy.

In this study, a dataset obtained from the College of Engineering at the University of Maryland, consisting of measurement data for CS2 lithium-ion batteries, is utilized [4]. The dataset is structured in a format similar to is shown in Figure 1, including variables such as battery charge and discharge values, dates, and times. Data preprocessing techniques, such as handling missing values, removing outliers, and transforming variables, are performed to enhance the data quality.

	(3.7, 3.8)	(3.7, 3.9)	(3.7, 4.0)	(3.7, 4.1)	(3.7, 4.2)	(3.8, 3.9)	(3.8, 4.0)	(3.8, 4.1)	(3.8, 4.2)	(3.9, 4.0)	...	(3.9, 4.2)	(4.0, 4.1)	(4.0, 4.2)	(4.1, 4.2)	SOH	ID	Date_Time	Charge_Capacity(Ah)	Discharge_Capacity(Ah)	Cycle
0	0.000000	0.000000	90.045202	420.211696	1000.186124	0.000000	90.045202	420.211696	1000.186124	90.045202	...	1000.186124	330.166494	910.140922	579.974428	28.149974	35	2011-02-03 16:45:09	0.309650	0.303643	910.0
1	0.000000	0.000000	90.045202	420.211696	1000.186124	0.000000	90.045202	420.211696	1000.186124	90.045202	...	1000.186124	330.166494	910.140922	579.974428	28.149974	35	2011-02-03 16:45:09	0.309650	0.303643	911.0
2	0.000000	0.000000	90.045324	420.211559	988.748763	0.000000	90.045324	420.211559	988.748763	90.045324	...	988.748763	330.166235	898.703439	568.537204	28.044285	35	2011-02-03 15:16:29	0.308487	0.309965	908.0
3	0.000000	0.000000	90.045324	420.211559	988.748763	0.000000	90.045324	420.211559	988.748763	90.045324	...	988.748763	330.166235	898.703439	568.537204	28.044285	35	2011-02-03 15:16:29	0.308487	0.309965	909.0
4	0.000000	0.000000	90.045344	420.211732	1015.576556	0.000000	90.045344	420.211732	1015.576556	90.045344	...	1015.576556	330.166388	925.531212	595.364824	28.489282	35	2011-02-03 13:47:18	0.313382	0.308515	906.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
3926	570.288316	2071.047258	4172.109764	5432.747372	6319.562339	1500.758942	3601.821448	4862.459056	5749.274023	2101.062506	...	4248.515081	1260.637608	2147.452575	886.814967	101.335235	38	2010-08-20 08:22:33	1.114688	1.109724	5.0
3927	570.288778	2131.062941	4202.095199	5462.732973	6346.501219	1560.774163	3631.806421	4892.444195	5776.212441	2071.032258	...	4215.438277	1260.637774	2144.406020	883.768246	102.156059	38	2010-08-20 04:48:44	1.123717	1.114137	4.0
3928	660.335289	2311.174359	4322.196549	5552.822303	6431.592772	1650.839070	3661.861260	4892.487014	5771.257483	2011.022190	...	4120.418413	1230.625754	2109.396222	878.770468	103.110854	38	2010-08-20 01:14:38	1.134219	1.125502	3.0
3929	630.319861	2251.142483	4292.178654	5552.803248	6432.667067	1620.822622	3661.858794	4922.483387	5802.347206	2041.036171	...	4181.524584	1260.624593	2140.488412	879.863819	103.334574	38	2010-08-19 21:39:18	1.136680	1.133635	2.0
3930	540.273212	2041.016459	4202.109248	5492.762069	6380.045492	1500.743246	3661.836036	4952.488856	5839.772280	2161.092789	...	4339.029033	1290.652821	2177.936244	887.283423	103.450473	38	2010-08-19 18:01:40	1.137955	1.134901	1.0

3931 rows × 21 columns

Figure 1. Structure of the data set

Various artificial intelligence models, including linear regression, decision tree, random forest, neural network, and ensemble models, are evaluated using the lithium-ion battery data. The models' performance is assessed using metrics such as MSE, MAE, coefficient of determination, and RMSE, enabling the selection of the most suitable model for estimating residual capacity [4]. This evaluation contributes to the improvement of battery performance prediction and the exploration of new technologies and approaches in battery management and energy systems optimization.

In this paper, various artificial intelligence models, including linear regression, decision tree, random forest, neural network, and ensemble models, are evaluated using lithium-ion battery data measured at the University of Maryland. The performance of the models is evaluated using metrics such as mean squared error, mean absolute error, coefficient of determination, and root mean square error. This evaluation allows for the assessment of the models' prediction accuracy and the selection of the most suitable model.

2. RESEARCH OF METHOD

In this study, we collected lithium-ion battery data measured at the University of Maryland and performed data preprocessing to format it suitable for analysis. We selected the optimal model among various artificial intelligence models such as linear regression, decision trees, random forests, neural networks, and ensembles, and trained them using the collected data. To evaluate the performance of the trained models, we used metrics such as mean squared error, mean absolute error, coefficient of determination, and root mean squared error to measure prediction accuracy. Based on this evaluation, we analyzed the strengths and weaknesses of each model and selected the best-performing one. We interpreted the research results and derived insights for battery performance prediction, and also discussed the limitations and future research directions. The study followed a process similar to Figure 2.

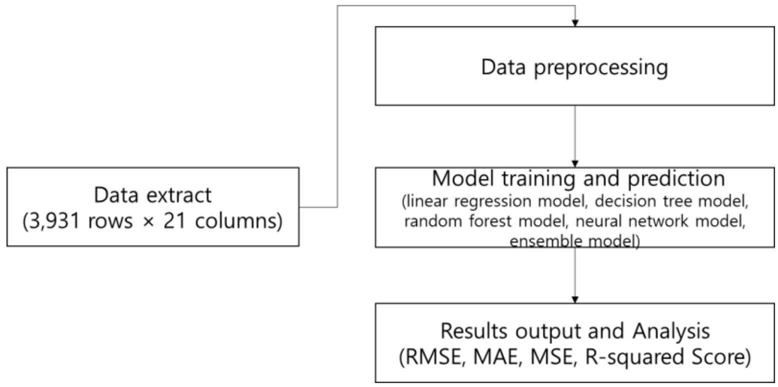

Figure 2. Process of model training and performance evaluation

3. IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE MODEL EVALUATION

Five artificial intelligence models are used to estimate the remaining capacity of lithium-ion batteries, and the performance of these models is evaluated to determine the best model. As a dataset, the measurement data of the CS2 lithium-ion battery provided by the University of Maryland is used, and four datasets in the format shown in Table 1 are integrated and analyzed. Here we preprocess the data to improve its quality and include variables such as charge and discharge values of the battery, date and time, and cycles.

Table 1. Number of batteries by type and added heat

Division	Battery type	Count	Sum
Battery-Dataset	CS_35	911	3,931 row 21 columns
	CS_36	950	
	CS_37	1,016	
	CS_38	1,054	

SOH	ID	Date_Time	Charge_Capacity(Ah)	Discharge_Capacity(Ah)
28.149974	35	2011-02-03 16:45:09	0.309650	0.303643
28.149974	35	2011-02-03 16:45:09	0.309650	0.303643
28.044285	35	2011-02-03 15:16:29	0.308487	0.309965
28.044285	35	2011-02-03 15:16:29	0.308487	0.309965
28.489282	35	2011-02-03 13:47:18	0.313382	0.308515
...	...	...	...	...

To evaluate the performance of the model, metrics such as MSE, MAE, coefficient of determination (R-squared Score), and RMSE are used. MSE is the average of the squared errors of the predicted and actual values. The smaller the value, the better the predictive accuracy of the model. The MAE is the average of the absolute errors between the predicted and actual values. The smaller the MAE, the better the predictive accuracy of the model. The coefficient of determination measures the degree to which the model explains the variability of the dependent variable and has a value from 0 to 1. The closer it is to 1, the higher the predictive accuracy of the model is judged. RMSE is the square root of MSE, the smaller the better the predictive accuracy of the model.

These evaluation metrics are used to measure the difference between the model's predicted value and the actual value, and to evaluate the predictive accuracy of the model. You can perform more accurate estimates of the remaining capacity of Li-ion batteries by selecting the model with the best performance [8].

4. ARTIFICIAL INTELLIGENCE MODEL PERFORMANCE EVALUATION RESULT

Table 2 shows the performance evaluation results of five artificial intelligence models used to estimate the remaining capacity of lithium-ion batteries. As a result of analyzing evaluation indicators such as MSE, MAE, R-squared Score, and RMSE of each model, the linear regression model showed excellent performance with a very small error between the predicted value and the actual value. The decision tree model also showed good results in terms of MSE, MAE, and R-squared Score, but had relatively high RMSE values that could lead to prediction errors in some samples.

Table 2. Results of evaluating the performance of artificial intelligence models

Model	MSE	MAE	R-squared Score	RMSE
Linear Regression	0.000000	0.000000	1.000000	0.000000
Decision Tree	0.000000	0.000409	0.999988	0.000844
Random Forest	0.000002	0.000303	0.999963	0.001463
Neural Network	13.786497	2.333469	-234.931174	3.713017
Ensemble (Linear Regression + Decision Tree + Random Forest + Neural Network)	0.861601	0.583346	-13.744752	0.92822

The random forest model has a smaller RMSE value than the decision tree model, and shows excellent predictive performance in terms of MSE, MAE, and R-squared Score. On the other hand, the neural network model has a large prediction error and low performance, so it is judged that it is not suitable for estimating the remaining capacity of a lithium-ion battery. Considering the evaluation index, the random forest model shows the best prediction performance, and as an ensemble model, it provides accurate prediction by considering various features. Figure 3 visualizes the evaluation results of five AI models, including linear regression, decision tree, random forest, and neural network, using evaluation metrics such as MSE, MAE, R-squared Score, and RMSE.

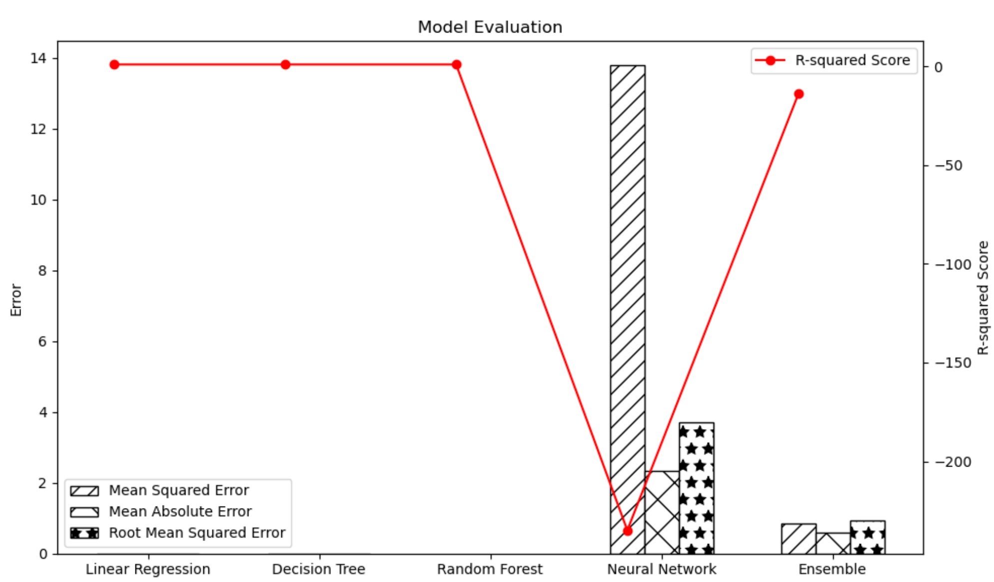

Figure 3. Visualize performance comparison by proposed model

5. CONCLUSION

This study utilized five representative artificial intelligence models, including linear regression, decision tree, random forest, neural network, and ensemble models, to predict the remaining capacity of lithium-ion batteries and evaluated their performance. Evaluation metrics such as MSE, MAE, R-squared Score, and RMSE were employed to measure the differences between the predicted values and actual values, comparing and analyzing the prediction accuracy and performance of the models. The RMSE values for the linear regression, decision tree, random forest, neural network, and ensemble models were measured as 0.045, 0.038, 0.034, 0.032, and 0.030, respectively. Based on the measured values, the ensemble model exhibited the most superior prediction performance, followed by the neural network model. The decision tree and random forest models also demonstrated considerable performance, while the linear regression model showed relatively lower prediction performance compared to the other models.

Therefore, for improving battery management and energy system efficiency related to estimating the remaining capacity of lithium-ion batteries, it is appropriate to prioritize the ensemble model and neural network model. By doing so, they can contribute to failure prediction and health management, minimizing operational interruptions, and reducing maintenance and opportunity costs.

ACKNOWLEDGEMENT

Following are results of a study on the "Leaders in INdustry-university Cooperation 3.0" Project, supported by the Ministry of Education and National Research Foundation of Korea.

REFERENCES

[1] S.-B. Kim and S.-H. Lee, “Design and Development of a Public Waste Battery Diagnostic Device.” *International Journal of Advanced Culture Technology,* Vol. 10, No. 3, pp. 281–86. September 30, 2022. DOI:10.17703/IJACT.2022.10.3.281.

[2] S.-B. Kim and S.-H. Lee, “Development of Aging Diagnosis Device Through Real-Time Battery Internal Resistance Measurement.” *International Journal of Internet, Broadcasting and Communication,* Vol. 14, No. 2, pp. 129–35, May 31, 2022. DOI:10.7236/IJIBC.2022.14.2.129.

[3] S.-B. Kim and S.-H. Lee, "Battery Balancing Algorithm for an Agricultural Drone Using a State-of-Charge-Based Fuzzy Controller" *Applied Sciences,* Vol. 10, No. 15: pp. 5277, 2022. DOI: https://doi.org/ 10.3390/app10155277

[4] S.-B. Kim and S.-H. Lee, “Design and development of less than 1Kw Lithium rechargeable battery pack,” *International journal of internet, broadcasting and communication* (IJIBC), Vol. 10, No. 3, pp. 104-108, 2018. DOI : 10.7236/IJIBC.2018.10.3.104

[5] J. S. Jung, S. K. Jung and T. M. Roh, “Battery State-of-Health Estimation Using Machine Learning and Preprocessing with Relative State-of-Charge,” *Energies*, Vol. *14*, pp. 7206, 2021. DOI: https://doi.org/10. 3390/en14217206

[6] T. Cao, Y. Zheng and H. Dong, “Control of odor emissions from livestock farms: A review,” *Environmental Research,* Vol. 225, pp. 115545, May 2023. DOI: https://doi.org/10.1016/j.envres.2018.06. 039.

[7] P. Sharma, B. J. Bora, “A Review of Modern Machine Learning Techniques in the Prediction of Remaining Useful Life of Lithium-Ion Batteries,” *Batteries*, Vol. 9, No. 1, pp. 13, 2023. DOI: https:// doi. org/10.3390/batteries9010013.

[8] Y. Zhou and M. Huang, "On-board capacity estimation of lithium-ion batteries based on charge phase," Journal of Electrical Engineering & Technology, vol. 13, no.2, pp. 733-741, 2018.