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Optimizing Battery Capacity Prediction Using Advanced Machine Learning Algorithms: A Comparative Analysis of LSTM, RNN, SVM, RF, and Kalman Filter

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Abstract: - Lithium-ion has important applications in portable devices, electric vehicles, and more recently, in large-scale energy storage systems. The prediction of battery capacity and remaining useful life or RUL is an important aspect which can be used in assuring reliability and safe operation of systems that employing batteries. In this research, the efficiency of different prospective algorithms: The technique involving the CALCE datasets for using LSTM, RNN, SVM, RF, and the Kalman Filter approach to predict the RUL of lithium-ion batteries is presented. The data will be further pre-processed depending upon the kind of look for non-linearity, as follows for all the models, their performance will hereby be checked with the help of the model validation on below said error: RMSE, MAE and Relative Error. The evaluation reveals that even though other models are good at enhancing the temporal dependencies of battery data, LSTM still performs better in terms of model accuracy and reliability of the temporal and non-linear relationships present in the battery data. The relevance of this research arises from the ability to establish suitable areas in applying machine learning strategies to IBMSs and enhance the performance and reliability of Li-ion batteries.

Keywords*:* Lithium-ion batteries, Battery capacity prediction, Remaining useful life (RUL), Predictive algorithms, Machine learning strategies, Li-ion battery performance

1. Introduction

Lithium-ion batteries have become standard equipment for portable electronics and electric vehicles, and have created the market for extra-large-scale renewable power and energy storage. Now, let us consider the size of lithium-ion battery market worldwide which as for the given period reached $36 [1]. The current estimated of the market is nearly about 7 billion in the year 2019, it has a good potential to grow up to around about 129 [1]. Estimated to reduce to $ 3 billion by the year 2027 with the growth rate of 18 % [1]. Or in the range of 2020 to 2027, it was 0% decrease [1].

The need for an optimized battery management system, which is often referred to as BMS – Battery Management Systems – rises when demand increases by such a great margin [2], discusses BMS, including voltage and current monitoring, charge estimation, thermal management, and data actuation and storage. However, Lithium-ion battery has some shortcomings, one of which is the deterioration process that causes decrease of its capacity and raise of possibilities of failure [3,5,6], In the course of cycling, it was observed that capability of batteries declined with time due to inefficiency in the charging and discharging cycle [4,8,9] and also; the exposed battery's safety to various dangers. As these batteries are used in various gadgets accurately determining the RUL is very crucial since it can help in making sure that the devices taking power from these batteries are safe to be operated [3,10,11].

Nonetheless, it is challenging to predict RUL since, different natures of degradation are not always linear [3] such as the situation with bearings varies from linear to logarithmic. Therefore, non-linear degradation is more complex than the linear degradation that is founded on the battery capacity deterioration linearly proportional to time and shifts in the battery capacity that cannot be explained by a linear model depending on time as well as considering the influences of temperature, charge/discharge rates, and chemical reactions in the battery. These issues require complex forecasts that are also able to handle degradations acquired with non-linear associative values [3].

[4], provides overview of battery degradation, focusing on the coupling between various mechanisms, physical and chemical approaches, and computational models. [5], reviewes discusses theoretical electrochemical and thermal models for predicting lithium-ion battery performance, focusing on separators. It highlights their crucial role in safety and performance, and suggests further simulations for optimization. [6], explores battery models, machine learning, and meta heuristic algorithms, focusing on lithium-ion batteries and their charging and discharging characteristics.

[7], reviews state-of-the-art ML-based data-driven fault detection/diagnosis techniques for (LIBs), providing a reference for researchers to develop accurate, reliable, and adaptive strategies for LIB fault diagnosis, while also discussing current and future challenges. [8], proposes method extracts voltage-dependent health features from partial voltage profiles and uses battery degradation data for accuracy. [9], A new method, Auto-CNN-LSTM, is proposed for accurately predicting the remaining useful life of lithium-ion batteries, reducing maintenance and accidents. Experiments show its effectiveness.

[10], model outperforms other models, achieving accurate predictions and reliable uncertainty quantification. [11], proposes a novel approach for RUL estimation, based on deep neural architecture due to its great success in sequence learning. [12], presents a novel capacity estimation method for lithium-ion cells in electric vehicles, combining model-based and data-driven methods using a sequential extended Kalman filter. [13], Embed-RUL is a novel approach for estimating the remaining useful life (RUL) of a system or machine from sensor data, using a sequence-to-sequence model based on Recurrent Neural Networks.

[14], presents the first full end-to-end deep learning framework for the swift prediction of lithium-ion battery remaining useful life. [15], proposes a hybrid ensemble data-driven method for accurately predicting the state-of-health (SOH) and RUL) of Li-ion batteries. [16], propose a Personalized Transformer model, which outperforms SASRec by almost 5% on real-world datasets.

[17], proposes an Autoencoder Gated Recurrent Unit (AE-GRU) model for predicting Remaining Useful Life (RUL) in smart manufacturing equipment.[18], The paper proposes an attention mechanism-based Convolutional Neural Network (CNN) with positional encoding for accurate Remaining Useful Life (RUL) prediction of lithium-ion batteries, overcoming the time-consuming nature of Recurrent Neural Networks. [19], is a novel RUL prediction technique using long short-term memory (LSTM) for lithium-ion batteries.

[20], reviews battery prognostics and health management (PHM) studies, focusing on lithium-ion batteries. The study highlights the increasing number of publications on battery PHM in the past decade, emphasizing the need for accurate health estimation and high availability. [21], a sequential recommendation model called BERT4Rec, which uses deep bidirectional self-attention to model user behavior sequences.

[22], introduces a neural network to model battery degradation trends and uses a bat-based particle filter to optimize particle distribution. [23], A novel attentive recurrent network is proposed, outperforming deep models. [24], Experimental results on QUORA and MSCOCO datasets establish a new benchmark for paraphrase generation. [25], reviews vibration-based indicators for bearing and gear health, highlighting problems and areas for future study.

[26], proposes a fusion RUL prediction approach for lithium-ion batteries, utilizing Deep Belief Network and Relevance Vector Machine, demonstrating higher accuracy and stable performance compared to standard methods. [27], a data-driven approach to estimate the state-of-health (SOH) of electric vehicles' batteries, using real-world driving patterns and historical distributions of BMS data, resulting in highly accurate results with an average error of less than 2.18%. [28], A Gaussian model, genetic algorithm, Akaike information criterion, CDKF, and lithium-ion battery datasets are used to accurately estimate SoE, with a maximum error within 1%.

This study aims to address this non-linear degradation by evaluating the effectiveness of various predictive algorithms in estimating the RUL of lithium-ion batteries using the CALCE dataset over the following objectives.

1. Evaluate and compare different algorithms (model-based, data-driven, deep learning) for predicting the Remaining Useful Life (RUL) of lithium-ion batteries [8,12,13].
2. Examine the non-linear degradation patterns in the CALCE dataset [dataset] and evaluate how effectively each algorithm captures these patterns [9,14,15].
3. Assess the accuracy of predictive models using metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Relative Error (RE) [10,16,17].

2. Dataset Considerations

The CALCE dataset is sourced from the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland, a leading research center in reliability engineering and electronics [29]. CALCE is renowned for its comprehensive research in the field of battery technology, providing high-quality, extensively validated data that is widely used in academia and industry for various battery performance and reliability studies [29]. The data was meticulously collected under controlled laboratory conditions to ensure the accuracy and reliability of the results.

The batteries were subjected to various tests, including capacity test, temperature variations, discharge rates, cycle life tests. For the purposes of this research, battery sets from the initial capacity tests to the constant temperature of 25°C, are considered for which the RUL is estimated [29]. This specific subset of data provides a baseline understanding of the battery performance under standard conditions, allowing for a controlled analysis of the thermal propagation and other relevant parameters.

The dataset includes data on the INR 18650-20R lithium-ion battery [29] with a Lithium Nickel Manganese Cobalt Oxide (NMC) battery chemistry, which is a popular choice for many applications due to its high energy density and reliable performance. The specifications of the INR 18650-20R battery are shown in the table I. And the figure (1) represents the state condition of the CALCE battery dataset for the capacity, resistance, constant current constant time and constant voltage constant time with respect to the number of cycles of the battery [29].

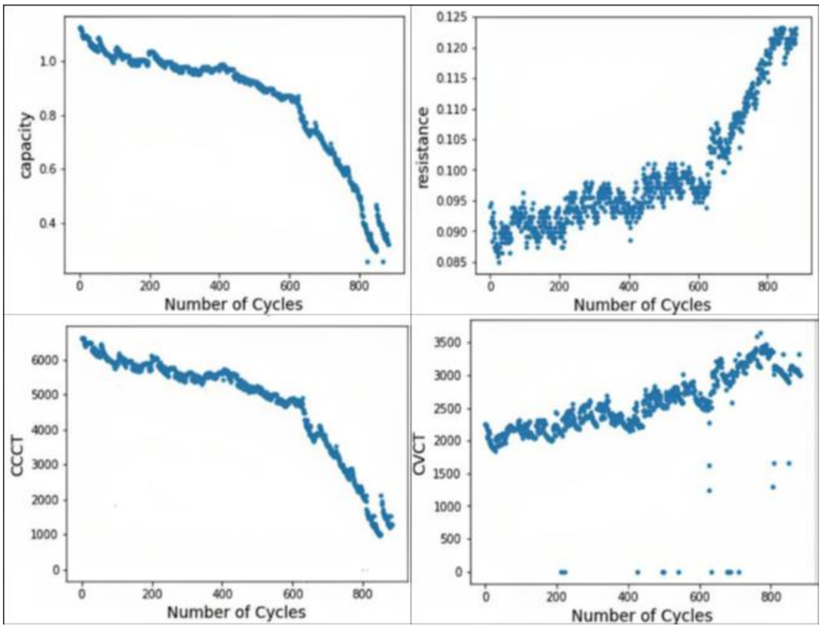

Figure 1. CALCE dataset Specifications

TABLE I. CALCE DATASET SPECIFICATIONS [29]

Nominal Capacity [29]	2000 mAh
Nominal Voltage [29]	3.6 V

Charge Cut-off Voltage [29]	4.2 V
Discharge Cut-off Voltage [29]	2.5 V
Maximum Continuous Discharge Current [29]	22A
Standard Charge Current [29]	1.0 A (0.5 C rate)
Standard Discharge Current [29]	4.0 A (2 C rate)

3. Methods

Within this study, the five approaches of estimating the RUL of lithium-ion batteries are described, namely; model-based, data-driven, and deep learning algorithms. Analyzing the model-based, data-driven, and deep learning algorithm's characteristics, it is possible to conclude that all types of algorithms are effective for some aspects of the RUL prediction. The use of all three methodologies – model-based, data-driven, and deep learning-based – allows for a detailed understanding of non-linear degradation patterns observed in the CALCE dataset [29].

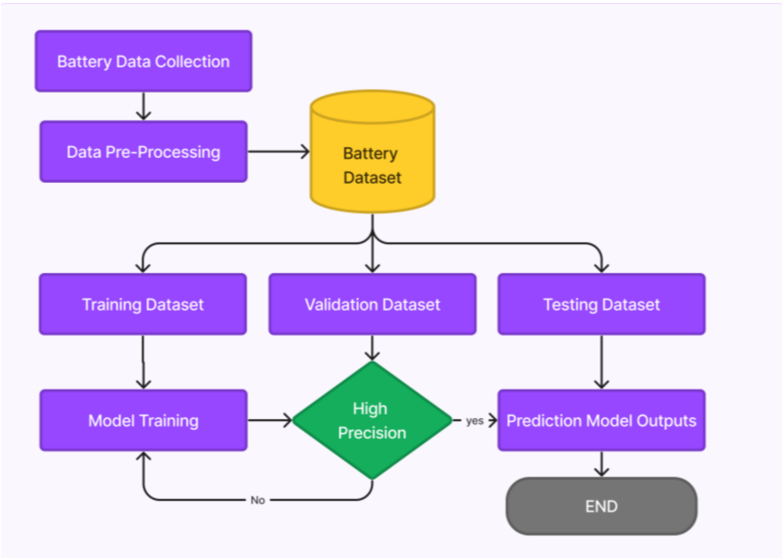

Figure 2. Functional Flowchart of the Proposed Methodology

To build a clear model in order to design battery capacity you begin from collecting data on batteries. This data includes information like the number and kind of discharging of the battery and the temperature, voltage, current and capacity of the battery. It is then followed by pre-processing in which this initial data collected goes through a process to rid it of any irrelevancies that may hinder the analysis.

Some of these are tasks such as handling with the cases where some of the data is not available, and normalizing the data. Thirdly, after preparing the data, the data is transformed so that non-linear patterns can be well handled, ensuring that the data is useful in modeling complex relationships. The first and second order effects are resolved, and the raw data from Step 2 is reformatted into the final dataset. This dataset is then divided into three parts: This study involves a training set to train the model, a validation set to tweak the model and check whether its performance is good, and finally a test set to measure the model's efficiency in performing on the data that it has not encountered before.

Subsequently, the training is performed on different machine learning algorithms where an attempt is made to fine tune the settings of the model that is trained on the training data. After the training is done, it is done once more on the validation set to ensure that the model is quite accurate. If the traditional approaches do not give adequate results in the form of high accuracy, then the model is again passed through a few rounds of training. The final step in constructing the current model is to fine-tune it using the test set for estimating battery capacity; this allows the model to be tested on new data that the algorithm has not encountered before.

a. Prediction Algorithm

There are various algorithms available for predicting the RUL of lithium-ion batteries, broadly categorized into model-based, data-driven, and deep learning approaches. Each type of algorithm has its strengths and is chosen based on the specific requirements of the application [22] [23]. The choice of algorithms is specific to the prediction of RUL throughout the process.

Kalman Filter: It is a model-based algorithm which is used for continuous state estimation in dynamic systems [12,18]. They operate by recursively processing measurements over time, producing estimates of unknown variables that tend to be more precise than those based on a single measurement alone [12,18]. Effective in managing noisy data and providing real-time continuous estimates, which are crucial for predicting the state of charge and RUL in lithium-ion batteries. The Kalman filter can be determined from the Equation (1), where T_i *is the ith prediction.*

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \quad (1)$$

Random Forest Regression (RFR): is a data-driven model which is a robust machine learning algorithm that constructs multiple decision trees during training and outputs the mean prediction of the individual trees [27]. It is particularly adept at handling non-linear relationships and interactions between variables. Has the ability to handle large datasets and complex relationships makes it highly effective for non-linear RUL predictions [27]. Additionally, it is resistant to overfitting due to the ensemble nature of the model, which averages out biases it can be represented as in Equation (2), where T_i *is the ith prediction.*

$$y = \frac{1}{n}\sum_{i=1}^{N} T_i(x) \quad (2)$$

Support Vector Machines (SVM): Is also a data driven model which is powerful with classification and regression tasks, especially in high-dimensional spaces [7]. SVM works by finding the hyperplane that best divides a dataset into classes. It is expressed as in Equation (3), *where a and ȧ are Lagrange multipliers, K is RBF kernel function and b is base term.*

$$f(x) = \sum_{i=1}^{N}(a_i - \dot{a}_i)K(x_i, x) + b \quad (3)$$

Recurrent Neural Network (RNN): is a deep learning algorithm which is designed for sequence prediction problems [9,10,14,19]. They maintain a hidden state that is influenced by the previous time steps, making them suitable for temporal data. Capable of effectively capture temporal dependencies in sequential data, a crucial aspect for predicting the Remaining Useful Life (RUL) of batteries, where past states play a significant role in determining future states.

Long Short-Term Memory (LSTM): is also another deep learning algorithm which is a type of RNN network [9,10,13,14,19,22] specifically designed to overcome the vanishing gradient problem. They can capture long-term dependencies by using a more complex architecture. Its design includes memory cells and three types of gates (input, forget, and output gates) that control the flow of information, allowing them to retain and use information over longer periods effectively [9,10,14,19]. And excel in modeling long-term dependencies and are extensively utilized in diverse time-series prediction tasks, such as predicting the Remaining Useful Life (RUL) of batteries. Their ability to handle non-linear and complex patterns makes them superior for this application, it can be represented through the Equation (4)

$$\hat{y}_t = W_y \cdot h_t + b_y \quad (4)$$

Data Preprocessing can be performed through standardization and noise reduction techniques. Standardization is a process which ensures the data from the CALCE dataset [29] is suitable for analysis and modeling, several preprocessing steps were undertaken. Standardization was a critical step to normalize the capacity values of the INR 18650-20R battery between 0 and 1. This process is essential to eliminate the effects of differing scales and to improve the performance of machine learning models which can be done with normalization and scaling by using the Equation (5) and (6) respectively. Noice Reduction is used to improve the quality of the dataset and ensure the accuracy of subsequent analyses, various noise reduction techniques were employed through filtering and smoothing techniques which can be represented using Equation (7) and (8).

$$PE(t,2k) = \sin(t/10000^{2k/m}) \tag{5}$$

$$PE(t,2k+1) = \cos(t,1000^{2k/m}) \tag{6}$$

$$\mathrm{head_i} = \mathrm{Attention}\left(H^{l-1}W_Q^l, H^{l-1}W_K^l, H^{l-1}W_v^l\right) \tag{7}$$

$$\mathrm{Attention} = (Q, k, v) = \mathrm{soft\,max}\left(\frac{Qk^T}{\sqrt{d_h}}\right) \tag{8}$$

b. Training, Testing, and Validation:

The pre-processed dataset was divided into training and testing sets to facilitate the development and evaluation of predictive models, 70% of the data, is training set used to train the machine learning models. This set included a representative sample of data across various operating conditions. The remaining 30% of the data was reserved as the testing set to evaluate the performance of the trained models. This separation ensures that the models are tested on unseen data, providing an unbiased assessment of their predictive capabilities. The validation is done using metrics such as RMSE, MAE, and RE to quantify their accuracy and reliability. These metrics provide a comprehensive view of the model performance, accounting for both average error and variability.

RMSE measures the square root of the average of the squares of the errors, providing a sense of the magnitude of prediction errors [4-6,8]. Is expressed in the Equation (9), useful for identifying significant deviations between predicted and actual values. It is particularly relevant when large errors are particularly undesirable in the RUL predictions.

$$\mathbf{RMSE} = \sqrt{\frac{1}{n-T}\sum_{t=T+1}^{n}(x_t - \hat{x}_t)^2} \tag{9}$$

MAE measures the average of the absolute errors, providing a straightforward measure of prediction accuracy [4-6,8] expressed in the Equation (10), provides a direct measure of the average magnitude of errors without considering their direction.

$$\mathbf{MAE} = \frac{\mathbf{1}}{\mathbf{n-T}}\sum_{\mathbf{t=T+1}}^{\mathbf{n}}(\mathbf{x_t} - \hat{\mathbf{x}}_\mathbf{t})^\mathbf{2} \tag{10}$$

RE measures the absolute error as a percentage of the actual value, normalizing the error based on the scale of the actual values [4-6,8] and is expressed in the Equation (11), provides a normalized measure of error, making it useful for comparing errors across different scales.

$$\mathbf{RE} = \frac{|\mathbf{RUL^{pred}} - \mathbf{RUL^{true}}|}{\mathbf{RUL^{true}}} \tag{11}$$

4. Results and Discussion

This section discusses the performance results of different machine learning techniques applied with the aim of estimating the RUL of lithium-ion batteries. The assessed algorithms are the LSTM, RNN, SVM, RF, and Kalman Filter algorithms. The evaluation of each of these algorithms is done using the following indicators namely; Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Relative Error (RE). The Figures 3(a) to 3(d) represent the graphical representation between the true and predicted battery capacity of the CALCE battery dataset will all techniques.

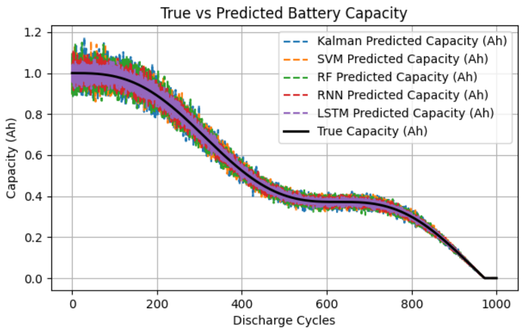

Figure 3(a). All Predictions vs True Capacity

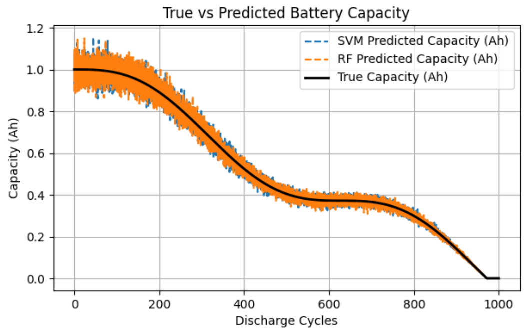

Figure 3(b). Kalman Filter Predictions vs True Capacity

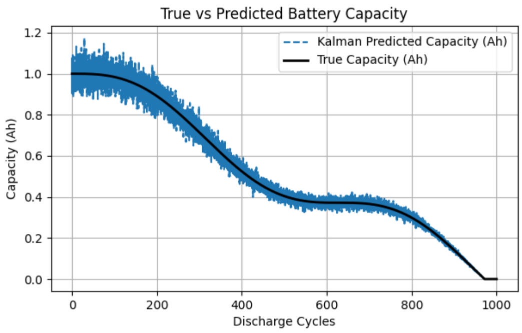

Figure 3(c). SVM and RF Predictions vs True Capacity

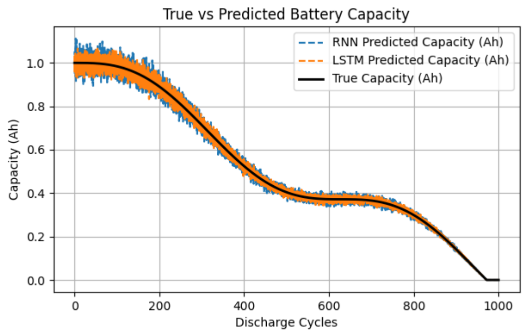

Figure 3(d). RNN and LSTM Prediction vs True Capacity

a. Non-Linearlity of the Battery Dataset

From the figures 3(a), 3(b), 3(c) and 3(d) we can observe that the power capability density versus cycle life at the initial stage (0 to about 200 cycles) exhibits a sharp decay. This phase signifies the rapid decline at the start for the indicated material. This initial drop is characteristic of lithium-ion batteries because something like the formation of the solid electrolyte interphase (SEI) will occur and just an initial stress on the materials which constitute the battery. Although it is still a rather steep decline, the capacity drops off at a slower and slower rate from approximately 200 to 600 discharge/charge cycles. This phase indicates a slope of linear degradation where the nature of the battery remains relatively constant and throughout a given phase. This means that the energy loss is slower than in the first phases or steps of the load-carrying process. After 600 and up to 800 cycles, the component exhibits almost constant or slightly decay capacity. Literally, this plateau signifies that, at the particular battery life cycle stage, the degradation process comes to a point where it stabilizes for some time. The battery is in the deep discharge/AGM stage and goes through slow cycling and has a slow rate of degrading during this time. On the matter of discharge cycles, the trend on the graph dips sharply after 800 cycles are completed. This accelerated degradation phase shows that the battery has come very close to the point where it cannot be used anymore. This is since during this phase, internal resistance raises as well, and as the rate of different degradation mechanisms such as, electrolyte breakdown and active material loss is high, results in a rapid feeble of the capacity.

b. Evaluation Process

Each model's prediction is compared with the error metrics of RMSE, MAE and RE for the listed algorithms. The table II, presents the performance metrics of various algorithms used for predicting the Battery RUL.

TABLE II. ERROR METRICS OF THE PREDICTION ALGORITHMS

Algorithm	RMSE	MAE	RE
RF	0.011993	0.008301	0.016101
SVM	0.006003	0.004153	0.007951
RNN	0.005985	0.004165	0.008068
Kalman	0.003010	0.002072	0.003974
LSTM	0.001202	0.000830	0.001598

The results prove that the Random Forest algorithm is the most inaccurate among the compared method, especially when it comes to the values of MAE, RMSE, and RE. Despite the capabilities of dealing with non-linearity and interaction of features, RF appears not very appropriate for this exact task because of the nature of being an ensemble method that could experience overfitting in the usage of battery data.

SVM comes to even par with RNN in terms of its results, with slightly lower MAE and RE, but a bit higher RMSE. SVM could thus be less powerful than the approaches based on neural networks in terms of modeling high non-linearity in battery characteristics. The RNN well performs, however, MAE, RMSE, and RE of the RNN algorithm is comparatively higher than LSTM and Kalman Filter. Linear connections in RNNs are also efficient in capturing short-term temporal relations, but when it comes to long-term temporal patterns, it may become a hindrance as the prediction error can be high.

The second in rank regarding accuracy is the well-known Kalman Filter. The error percentage yielded by the Kalman Filter is slightly higher than LSTM, yet it is far from being very high which proves the effectiveness of the model in predicting the battery capacity. Out of all the algorithms, LSTM algorithm has an outstanding performance indicated by low RMSE, MAE, and RE values. This further underscores the fact that LSTM performs better in predicting battery capacity in terms of accuracy because it is endowed with the capacity to detect the long-term dependencies and complex trends of the data set.

c. Rolling Errors:

To further illustrate the performance differences, the following plots in the figures 4(a), 4(b) and 4(c) for rolling errors of RMSE, MAE and RE respectively:

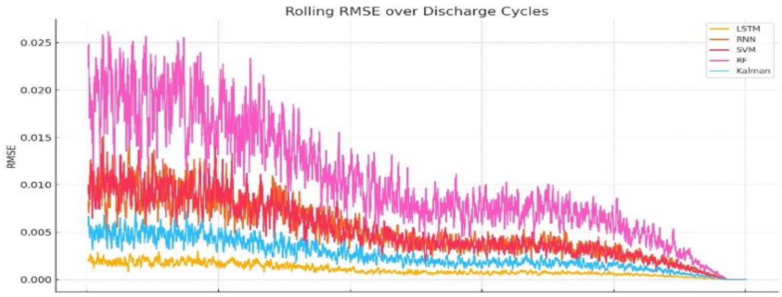

Figure 4(a). Rolling RMSE of the Predicted Algorithms

Rolling RMSE: A plot showing the rolling RMSE values over discharge cycles, highlighting LSTM's consistent performance as shown in Figure 4(a).

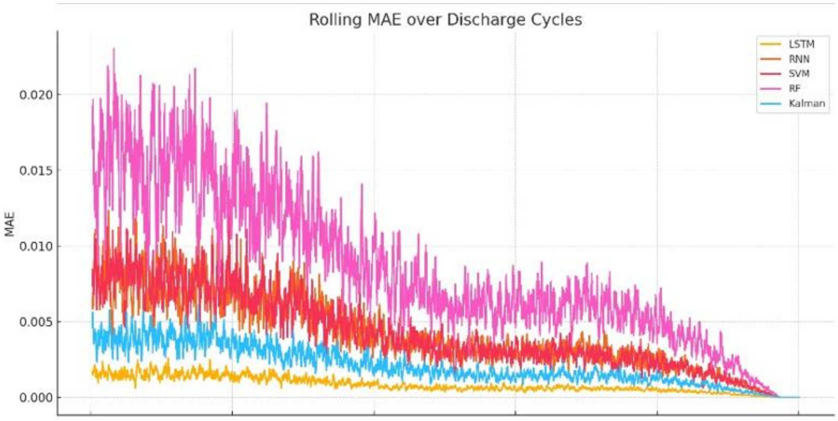

Figure 4(b). Rolling MAE of the Predicted Algorithms

Rolling MAE: A plot depicting the rolling MAE values over time, emphasizing LSTM's superior accuracy as shown in Figure 4(b).

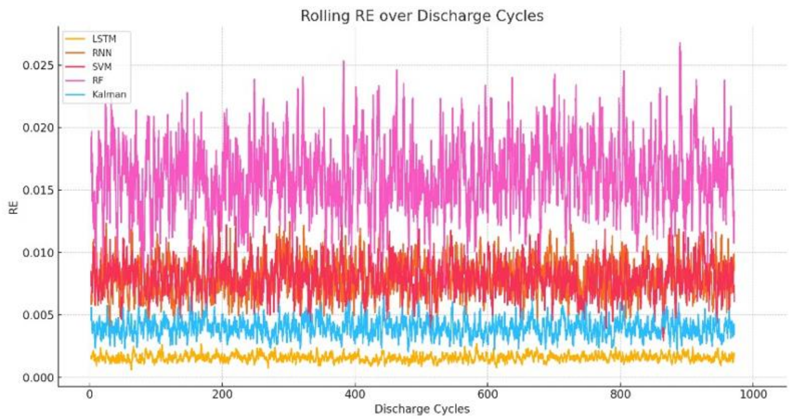

Figure 4(c). Rollig RE of the Predicted Algorithms

Rolling RE: A plot illustrating the rolling RE values, confirming LSTM's better prediction accuracy compared to other models as shown in Figure 4(c).

TABLE III. EFFICIENTY IMPROVEMENT OF LSTM OVER OTHER PREDICTION ALGORITHMS

Algorithm	RMSE	MAE	RE	RMSE percentage of change	MAE Percentage of change	RE Percentage of change
RF	0.011993	0.008301	0.016101	89.98%	90.00%	90.08%
SVM	0.006003	0.004153	0.007951	79.98%	80.02%	79.90%
RNN	0.005985	0.004165	0.008068	79.92%	80.07%	80.19%
Kalman	0.003010	0.002072	0.003974	60.08%	59.96%	59.78%

LSTM	0.001202	0.000830	0.001598	-	-	-

Table III shoes the efficientcy imporovemtn of the LSTM Algorithm over other Prediction Algorithms of RF, SVM, RNN, Kalman. For a range of 59% to 79% improvement can be observend from the table and when compared with the RF algorithm the LSTM is 90% efficient and have high prediction accuracy.

5. Conclusion

Five different techniques were considered in this study to compare their performance in predicting the remaining useful life of lithium-ion batteries: Long Short Term (LSTM), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), Random Forest (RF), and Kalman Filter. It is also evident from the results that the LSTM algorithm in all parameter manners bears the minimum RMSE, MAE, and RE values, which depicts high accuracy. This higher accuracy is due to LSTM's better capability in remembering long sequences in the data and modelling of non-linear relationships. The second optimized filter, known as the Kalman Filter also delivers optimal results but lesser than the LSTM in terms of precision. In terms of the accuracy, we can make the following conclusions The values of accurately classified instances for RNN and SVM are relatively high Compared with them, the performances of the proposed method, RF are relatively poor. The results provide a pointer that emphasis should be placed on choosing the right prediction algorithms given the nature of the battery data observed. This discovery can greatly improve the efficiency, reliability, and safety of the BMS by adopting the best algorithm possible to forecast the battery capacity utilizing LSTM among the more common alternatives in use.

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