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ANALYSING THE STATE OF HEALTH OF LITHIUM-ION BATTERIES USING ENSEMBLE EXTREME LEARNING METHOD

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ABSTRACT The state-of-health (SOH) estimation of lithium-ion batteries (LIBs) is of great importance to the safety of systems. In this, a novel ensemble learning method is proposed to accurately estimate the SOH of LIBs. The feature is defined as voltage, current, current capacity, and discharge capacity are extracted as the key health indicator for the LIBs. The Pearson correlation analysis is performed to select four optimal indicators that are used as inputs of the prediction model. A random learning algorithm named extreme learning machine (ELM) is applied to extract the mapping knowledge relationship between the health indicators and the SOH due to its fast-learning speed and efficient tuning mechanism. Moreover, an ensemble learning structure is proposed to reduce the prediction error of the ELM models. The accuracy and reliability of the estimation results are then markedly improved by creating a trustworthy decision-making rule to assess the veracity of the output of each individual ELM model and exclude unreliable outputs. The testing results on public data sets show that the proposed method can accurately estimate the SOH in 1 ms and is robust to the operating temperature. The lower root-mean-square error (RMSE) is as low as 0.78%. The proposed method does not require any additional hardware or downtime of the system, which makes the method suitable for online practical applications.

Keywords *– —ensemble extreme learning machine (ELM), lithium-ion battery (LIB), state of health (SOH) root-mean-square error (RMSE).*

1. INTRODUCTION

Due to their high energy densities, high nominal voltage, low self-discharge rate, low maintenance requirements, and relatively long lifespans, lithium-ion batteries (LIBs) have been used extensively in electric vehicles and energy storage systems. [1], [2]. However, as LIB ages and is affected by the working environment, its performance will inevitably decline over time [3]. The unexpected failure may result in emergent maintenance and unexpected system shutdown, which can be catastrophic. To achieve a satisfactory performance, it is crucial to precisely evaluate the state of health (SOH) of LIBs. The aging of LIB is a very intricate process. It can be generally summarized as the decomposition, precipitation, and lithium metal plating of the solid electrolyte interface, which results in capacity reduction and impedance increment [4]. Therefore, the capacity and impedance of LIB are two important indicators that can quantify the SOH. Various methods have been reported in recent years for the SOH estimate of LIB. Direct measurement methods, model-based methods, and data-driven methods can be used to classify these approaches. Direct measurement methods to calculate the capacity or impedance of battery cells based on direct measurements. Both the Coulomb-counting approach and the open-circuit voltage method [5] are frequently used to determine a battery's capacity. The internal relationship between the OCV relaxation curve and also the ability is used by the open-circuit voltage methodology to estimate the capacity [6]. In [7], the Coulomb-counting method is proposed to investigate the nonlinear aging characteristics of LIBs. Additionally, SOH can be detected by measuring the increase in battery impedance brought on by electrochemical processes throughout the aging process. The most used technique for determining a battery's impedance is electrochemical impedance spectroscopy [8]. In addition to the EIS method, the current pulses and the Joule effect are also applied to measure internal resistance [9]. In summary, a direct measurement method usually has less computational complexity but is hard to be implemented online and may require additional hardware.

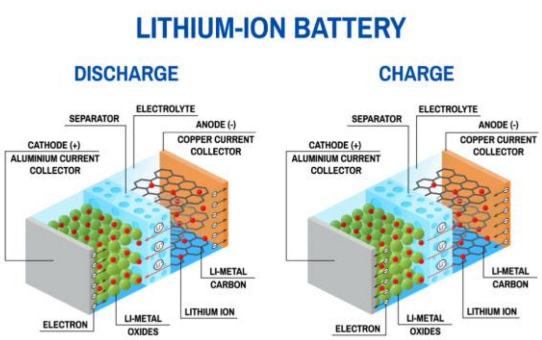

Fig.1: Example figure

The model-based methods use the electrochemical mechanism or equivalent electrical circuit to emulate the mathematical or stochastic models of the battery degradation phenomenon [10]. One of the model's parameters is the battery's capacity or impedance. The model parameters are identified to estimate health. Typically, the analogous model is simulated and the SOH is estimated using the Kalman filter [11], particle filter [12], and dual-sliding-mode observer [13]. Moreover, a probability density function in [14] is also proposed for estimating the SOH by analyzing the charging and discharging data of the battery.

2. LITERATURE REVIEW

Prognostics of lithium-ion batteries based on Dempster-Shafer theory and the Bayesian Monte Carlo method

A new method for state of health (SOH) and remaining useful life (RUL) estimations for lithium-ion batteries using Dempster–Shafer theory (DST) and the Bayesian Monte Carlo (BMC) method is proposed. This study develops an empirical model based on the way lithium-ion batteries degrade physically. Combining sets of training data based on DST allows for the initialization of the model's parameters. BMC then used the output data of the model parameters and predicted the RUL based on available data through battery capacity monitoring. The model becomes increasingly accurate at forecasting RUL as more data become available. This strategy is described in two case examples.

Data-driven prediction of battery cycle life before capacity degradation

Technology development must go more quickly if the lifetime of complicated, nonlinear systems like lithium-ion batteries is to be accurately predicted. Diverse aging mechanisms, high device heterogeneity, and changing, working environments continue to be important obstacles. With 124 commercial lithium iron phosphate/graphite cells cycled under fast-charging conditions and cycle lifetimes ranging from 150 to 2,300 cycles, we create a comprehensive dataset. We employ machine learning techniques to forecast and categorize cells by cycle life using discharge voltage curves from early cycles that have not yet shown a capacity decline. Our top models get a 9.1% test error for categorizing cycle life into two groups using the first five cycles and a 4.9% test error for forecasting cycle life quantitatively using the first 100 cycles (showing a median increase of 0.2% from baseline capacity). This research demonstrates the potential for predicting the behavior of complex dynamical systems by combining deliberate data production with data-driven modeling.

Prognostics of lithium-ion batteries based on relevance vectors and a conditional three-parameter capacity degradation mode

Lithium-ion batteries are widely used as power sources in commercial products, such as laptops, electric vehicles (EVs), and unmanned aerial vehicles (UAVs). In order to ensure a continuous power supply, the functionality and reliability of lithium-ion batteries have received considerable attention. In this study, a battery capacity prognosis approach is created to determine how long lithium-ion batteries will still be useful. A relevance vector machine and a conditional three-parameter capacity degradation model make up this capacity prognostic technique. The representative training vectors including the cycles of the relevance vectors and the predicted values at the cycles of the relevance vectors are found using the relevance vectors that are derived using the relevance vector machine. To fit the prediction values at the cycles of the relevance vectors, a conditional three-parameter capacity degradation model was created. Lithium-ion battery remaining useful life is calculated by extrapolating the conditional three-parameter capacity degradation model to a failure threshold. To validate the created method, three instance studies were done. The findings demonstrate the capability of the established technology to forecast lithium-ion battery health in the future.

Lithium-ion battery aging mechanisms and diagnosis method for automotive applications: Recent advances and perspectives

Lithium-ion batteries decay every time it is used. Degradation brought on by aging is unlikely to be reversed. Lithium-ion battery aging mechanisms are numerous and intricate, and they are intricately linked to a variety of interaction aspects, including battery types, electrochemical reaction stages, and operating circumstances. We extensively review the mechanisms and analysis of lithium-ion battery aging in this study. On the basis of the anode, cathode, and other battery structures, the effects of various internal side reactions on the degradation of lithium-ion batteries are studied with regard to the aging mechanism. It is discussed how many environmental elements affect the ageing process, with temperature having the biggest influence in comparison to other external factors. Three commonly utilized techniques are covered when it comes to aging diagnosis: disassembly-based post-mortem analysis, curve-based analysis, and model-based analysis. While curve-based analysis and model-based analysis offer quantitative analysis, post-mortem analysis is typically used for cross-validation. Insights are provided for creating online battery aging diagnosis and battery health management in the next generation of intelligent battery management systems on the basis of the difficulties in using quantitative diagnosis and onboard diagnostic on battery aging (BMSs).

3. METHODOLOGY

Compared with the model-based methods, data-driven methods do not require understanding the electrochemical principles of battery. However, many data-driven methods, such as support vector machine (SVM), often suffer from extended training time, heavy computational burden, and/or tedious tuning procedures, which reduce the efficiency of SOH estimation. Furthermore, estimation accuracy and reliability are also a concern for practical applications.

1. Suffer from extended training time
2. Heavy computational burden
3. and/or tedious tuning procedures, which reduce the efficiency

To overcome the drawbacks of long training time, heavy computational burden, and tedious tuning procedures of some data-driven methods, this article proposes a new fast ensemble learning method to estimate the cycling SOH of battery online with only one accessible and correlative health indicator.

1. The proposed method can accurately estimate the SOH in 1 ms and is robust to the operating temperature and load profile.

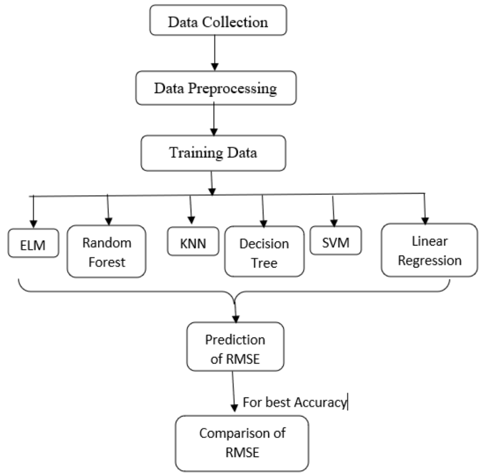

Fig.2: System architecture

MODULES:

To implement this project, we have designed the following modules

1) Upload Lithium CALCE Dataset; using this module we will upload the dataset to the application
2) Run Pearson Correlation: using this module we run the Pearson formula to calculate important attributes from the dataset and the attributes/column names which give a score of 1 will be considered an important attribute
3) Run Ensemble ELM Algorithm: using this module we will input the above dataset to a group or ensemble of ELM to train a model and then perform a prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
4) Run Random Forest Algorithm: using this module we will input the above dataset to Random Forest train a model and then perform prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
5) Run Decision Tree Algorithm: using this module we will input the above dataset to Decision Tree to train a model and then perform a prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
6) Run SVM Algorithm: using this module we will input the above dataset to SVM to train a model and then perform a prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
7) Run KNN Algorithm: using this module we will input the above dataset to KNN to train a model and then perform a prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
8) Run the Linear Regressor algorithm using this module we will input the above dataset to Linear Regressor to train a model and perform a prediction of battery health and check its prediction error rate with the original estimated values to get RMSE
9) Comparison Graph: using this module we will plot RMSE comparison between all algorithms and the algorithm with less RMSE is the better one

ALGORITHMS

ELM is a fast and robust machine-learning algorithm. The generalized single-layer feed-forward neural network (SLFN) was simply referred to as 2006–2008. The ELM theory is in favor of the assumption that learning models can be fed by randomness in the selection of input weights without any distribution-specific adjustment. An extreme learning machine (ELM) is a training algorithm for single hidden layer feedforward neural network (SLFN), which converges much faster than traditional methods and yields promising performance. fig.7

Random forest is a Supervised Machine Learning Algorithm that is used widely in Classification and Regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression. Fig.8

Decision trees use multiple algorithms to decide to split a node into two or more sub-nodes. The homogeneity of newly formed sub-nodes is increased by sub-node creation. In other words, we can say that the purity of the node increases with respect to the target variable. Fig.9

A supervised machine learning approach called "Support Vector Machine" (SVM) can be applied to classification and regression problems. However, it is mostly used in classification problems. Fig.11

The k-nearest neighbors (KNN) algorithm is a simple, supervised machine learning algorithm that can be used to solve both classification and regression problems. It's easy to implement and understand but has a major drawback of becoming significantly slow as the size of that data in use grows. Fig.10

4. IMPLEMENTATION

In this, we are in estimating the state of health (SOH refers to the life of the battery) of lithium batteries by using machine learning algorithms as its health is important to the safety of the system. Early prediction of battery health allows humans to replace the battery on time and the system can be protected. In the proposed, we are using the Pearson correlation formula to find out important attributes from the dataset and then using an Ensemble or group of ELM (extreme learning machines) algorithm to train a model and this model can be used to predict the SOH of the battery.

Has evaluated the performance of ELM in terms of RMSE error which refers to the error rate of prediction. The lower the prediction error rate the better the algorithm. We have compared ELM RMSE with Random Forest, SVM, KNN, decision tree, etc. In all algorithms propose Ensemble ELM gives less error rate.

To implement this project author has used the ‘CALCE Dataset’ which contains battery charging, voltage, battery discharge, etc. by using this dataset values we will train all algorithms and compare their performance. Below screen showing dataset details. fig.3

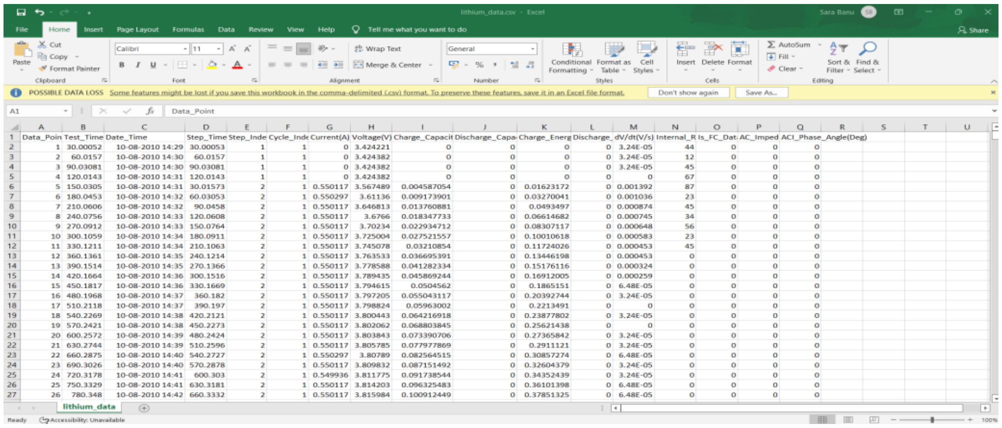

Fig.3: Dataset

5. EXPERIMENTAL RESULTS

Fig.4: Home screen

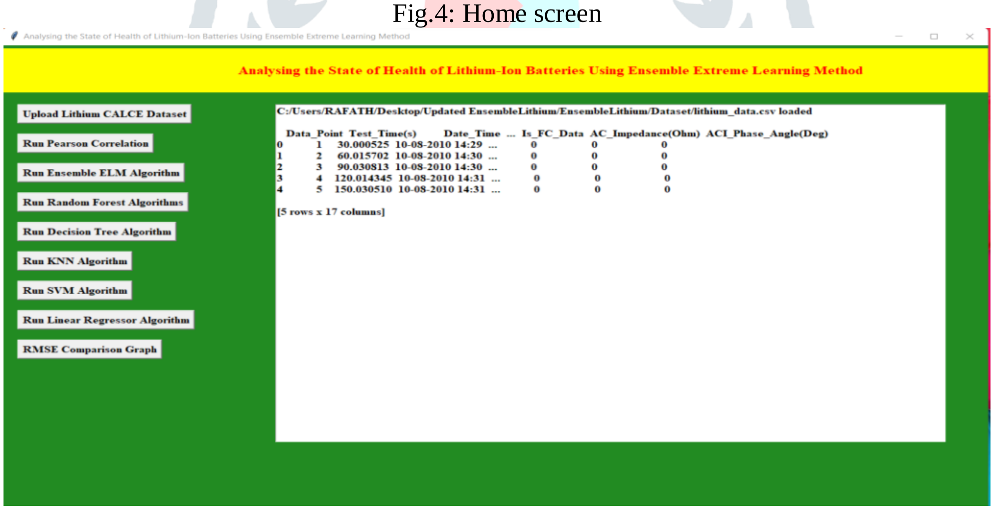

Fig.5: Lithium Calce dataset loaded

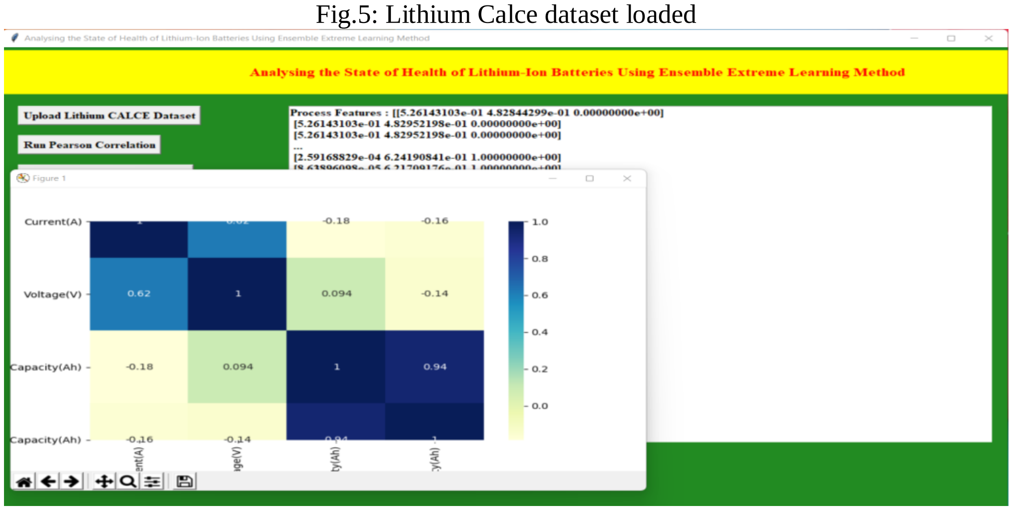

Fig.6: Pearson correlation

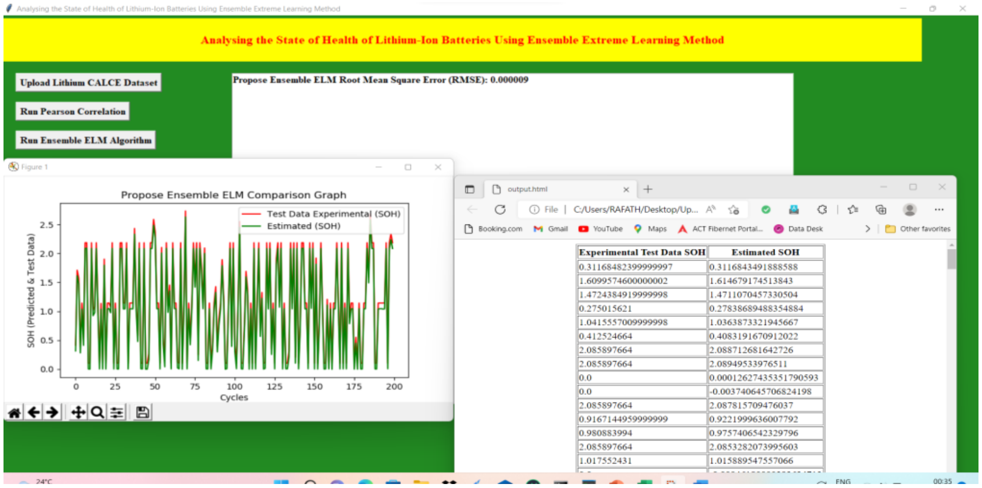

Fig.7: Ensemble EML algorithm

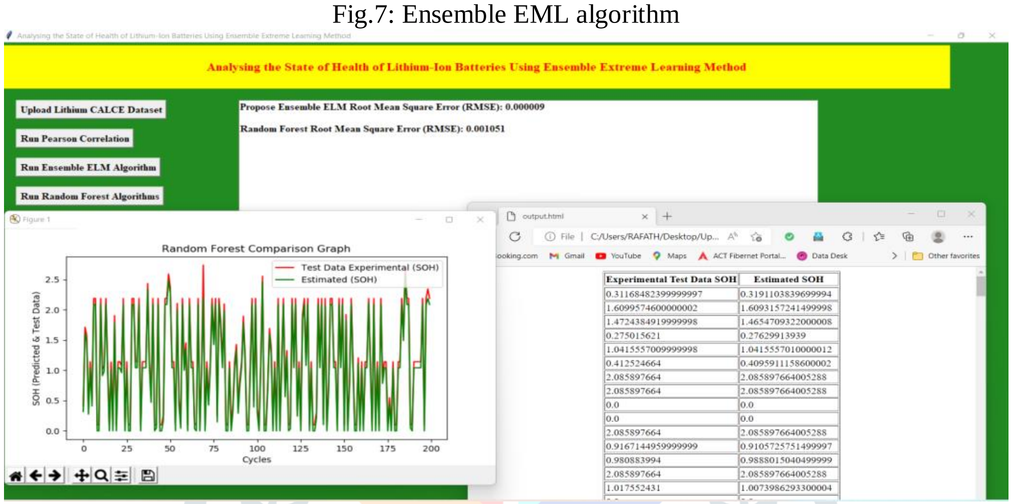

Fig.8: Random Forest algorithm

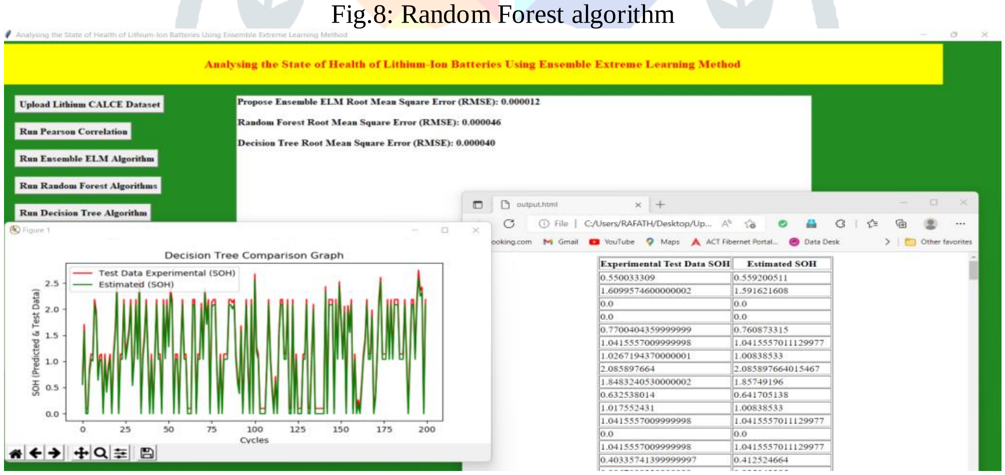

Fig.9: Decision tree algorithm

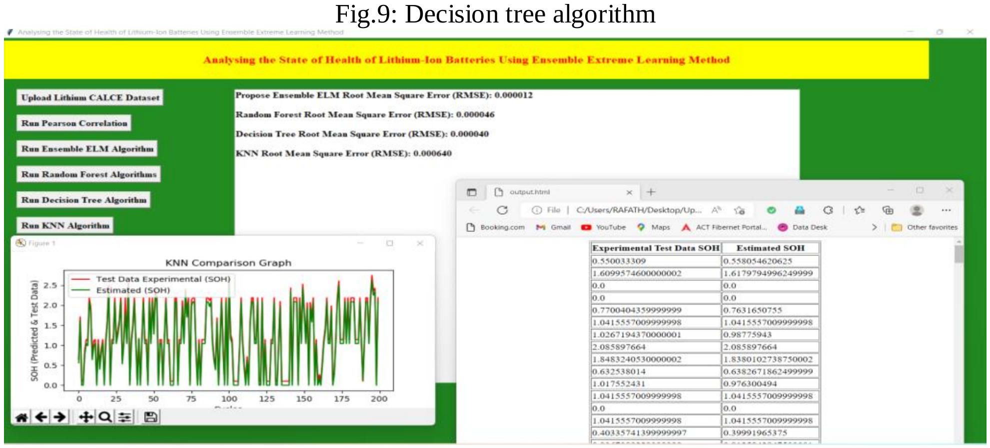

Fig.10: KNN algorithm

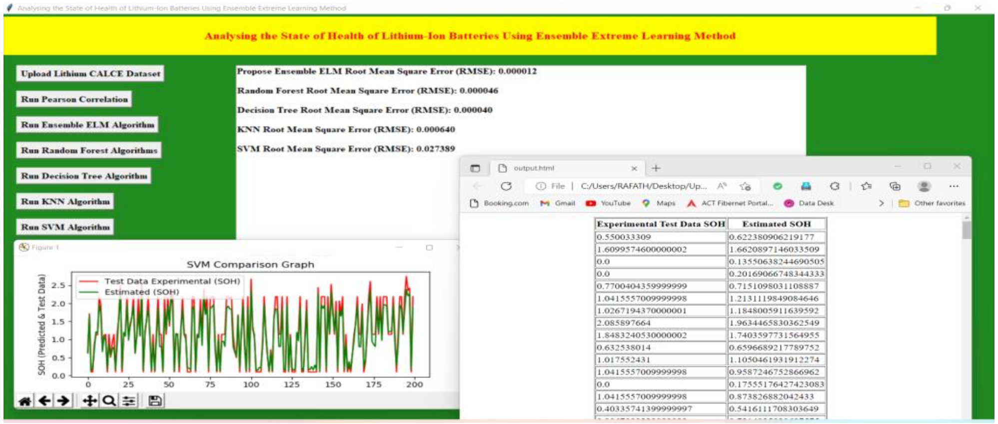

Fig.11: SVM algorithm

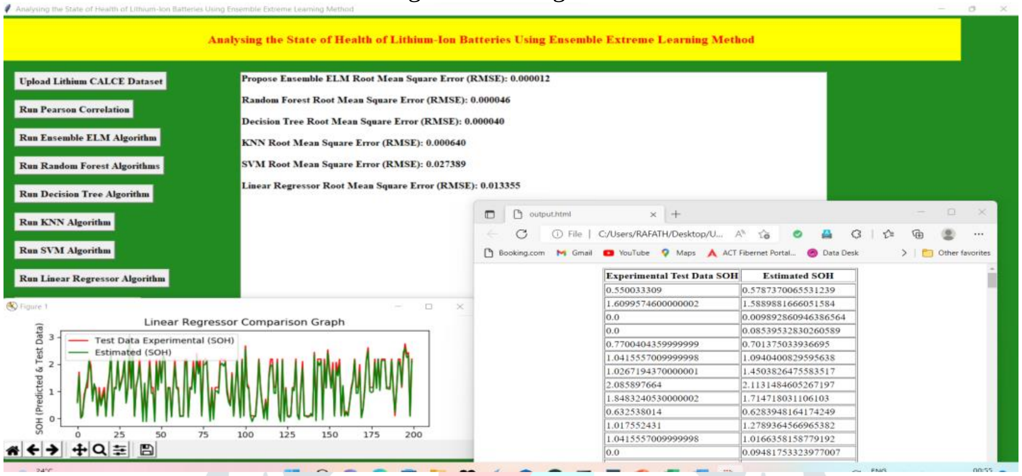

Fig.12: Linear Regressor algorithm

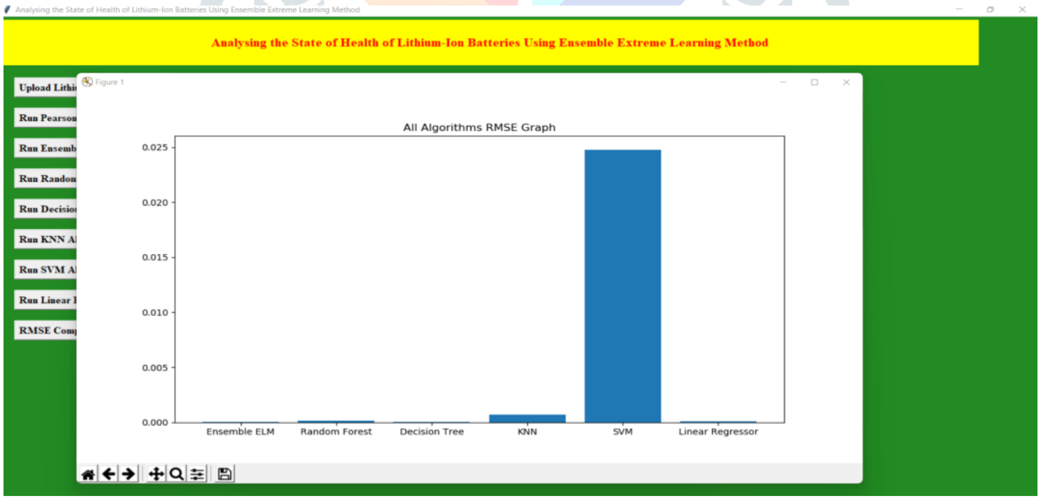

Fig.13: Comparison graph

6. CONCLUSION

A new data-driven method based on an ensemble Extreme Learning Machine for (SOH) estimation of (LIBs) is proposed. A health indicator extracted from the charging voltage signal is used to reflect the battery's health due to its strong linear relationship with the (SOH) of the battery. Four optimal voltage, current, current capacity, and discharge capacity parameters are integrated as the prediction features of (ELM) according to the Pearson correlation analysis. (ELM) is applied as a predictor to learn the knowledge relationship between features and (SOH), due to its merit of fast and accurate learning. An ensemble (ELM) learning structure is designed to improve the accuracy and stability of the prediction results. Finally, the standard data from (CALCE) are introduced to verify the effectiveness of the proposed (SOH) estimation method. The estimation results show that the proposed ensemble (ELM) based data-driven method can accurately and reliably estimate the (SOH) using a health indicator extracted from a small voltage range. The proposed (RMSE) value gives a less error rate.

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