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Hybrid Random Forest Regression and Artificial Neural Networks for Modelling and Monitoring the State of Health of Li-Ion Battery

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***Abstract:* -** Lithium-ion batteries play a significant role in modern energy storage systems for a number of applications, including renewable energy installations, electric cars, and portable devices. In order to guarantee the long-term dependability and safety of these battery packs, comprehensive modelling and monitoring approaches are required for accurate State of Health (SoH) evaluation. This research suggests an innovative strategy that combines the strengths of Random Forest Regression (RFR) and Artificial Neural Networks (ANN) for reliable Li-ion battery SoH modelling and monitoring. The research starts with the collection of thorough Li-ion battery data, which includes voltage, current, temperature, and cycling characteristics. The battery dataset's nonlinear relationships are captured utilising RFR as the main modelling method. In terms of feature selection and prediction precision, RFR's ensemble of decision trees shines, making it a strong contender for modelling complex battery behaviour. The SoH prediction is then enhanced by the use of ANN, a deep learning framework renowned for its ability to extract detailed patterns from data. The characteristics of RFR are complemented by ANN's capacity to discover hidden features and nonlinear correlations, improving the overall prediction performance. The suggested hybrid approach, that combines RFR and ANN, is trained and verified utilising a diverse database acquired from Li-ion battery sources under operational circumstances. To assess the prediction accuracy of a suggested framework measures like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R2) values are employed. The outcomes show that the hybrid RFR-ANN model works better than the individual RFR and ANN models, producing better SoH predictions. A viable solution for real-time Li-ion battery health monitoring is provided by this combination of conventional ML and deep learning approaches, which demonstrates the synergy among complexity and interpretability. This research advances battery SoH assessment and paves the way for the practical incorporation of precise monitoring systems into applications like electric vehicles, where timely and accurate SoH data is essential for maximising battery performance and extending operational lifespan.

Keywords: Li-ion batteries; State of Health (SoH); Random Forest Regression; Artificial Neural Networks (ANN); Battery Health Monitoring; Predictive Modelling

I. INTRODUCTION

The strength of lithium batteries lies in their ability to store significant amounts of energy. Moreover, their operation is uncomplicated, and they allow for repeated use in both charging and discharging the energy they hold. That is the reason why they are utilized in various objects such as automobiles, mobile devices, and unmanned aerial vehicles. So, it is important to keep track of how something is getting worse and evaluate how well it is working. Inside lithium batteries, a chemical reaction takes place to transform electrical energy into chemical energy. This allows them to store and release energy [1]. So, lithium batteries behave in complicated ways and are hard to understand and predict. The usual practice involves measuring a battery's wellness by evaluating its ability to gradually release energy. Afterwards, it examines the battery's degradation by examining data from its previous usage, and utilize diverse approaches to evaluate and anticipate its current state. In practical situations, it frequently lacks the full understanding of how a battery will deteriorate with the passage of time. It's also difficult to measure how much power the battery can hold when it's discharged, and it's hard to determine how quickly the battery ages. Consequently, there is a need for a more uncomplicated approach to appraise the battery's wellbeing and anticipate its potential usage duration. The maintenance of Li-ion batteries is vital for the consistent effectiveness and reliability of equipment [2].

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Across time, numerous specialists have examined the decline of batteries, techniques for monitoring their status, and strategies for predicting their future performance. Through the utilization of particle filters, Saha et al. made an estimation on the remaining duration of battery usage before it ceases to function [3], [4]. Xing et al. combines a regression model that uses data and equations to predict battery degradation over time. Furthermore, it utilizes a particle filter to monitor and record the deterioration trend [5] The analysis of grey, optimized correlation vector machine technique, comparing the discharge voltage at the same time, capacity, discharge voltage over time in a monotone echo state network procedure, and discharge voltage at the same time were all put together by Liu et al. [6] to monitor the lithium-ion battery's deterioration. Anode, cathode, and electrolyte are all contained within a protective case and are separated from one another by a porous separator in a lithium-ion (Li-ion) battery. Li-ions go from the anode to the cathode to store electrical energy during charging, whereas during discharge, the process is reversed and the gadget is powered [7].

Lithium-ion batteries are renowned for having a high-power density, a long cycle life, a low self-discharge ratio, and adaptability across a range of applications. Even with their benefits, batteries require careful handling and monitoring to avoid safety issues like thermal runaway, which can happen if the battery is damaged or charged incorrectly [8]. This emphasises the significance of continued research to improve both performance and safety aspects. To forecast battery capacity deterioration and residual lifespan [9]. The study outlines a procedure to assess the remaining useful life of batteries, as suggested by Mao [10].

In prior research, scientists primarily focused on specific metrics such as capacity, voltage, impedance, etc.) taken from data about how lithium batteries break down. The data was utilized to generate a model that forecasts the duration of the battery. Subsequently, Health Indicators and alternative techniques were employed to appraise the state of lithium batteries and determine their estimated remaining lifespan. It proceeded to provide these research findings to others as a beneficial asset. Lack of information regarding the batteries prevents us from acquiring a reference model. This factor complicates the ability to anticipate and measure the battery's decline. The battery's deterioration is caused by complex internal chemical and material factors, making the process non-linear and uneven. In any given situation, it is unachievable to consistently obtain an exact depiction of how the battery's lifespan will degrade. Several factors contribute to the increased difficulty in utilizing online predictions. In order to address these issues, the study's suggested system concentrates on the creation of a thorough remedy for modelling and tracking the SoH of Li-ion battery, addressing the critical requirement for battery reliability and performance in applications ranging from electric vehicles to renewable energy systems. The system's central component combines the advantages of RFR and ANN to produce a potent hybrid model. The system includes crucial elements like data gathering and preprocessing methods like Min-Max normalisation to guarantee data compatibility and consistency. With an emphasis on well-established, rigorous model training, optimisation, and performance evaluation will be carried out. Additionally, the approach is made to make it simple for the trained models to be seamlessly integrated into real-time battery management systems, providing continuous and precise SoH monitoring in useful, real-world settings. The system is being developed with the utmost ethical care and safety precautions, guaranteeing data protection, privacy, and prudent battery management. It is anticipated that this suggested system will lead to improvements in battery management dependability, increased practical applicability in crucial industries, and significant contributions to the field of battery technology and sustainable energy sources. This study's unique methodology of fusing RFR and ANN into a hybrid model, its extensive data collecting and preprocessing techniques, its rigorous performance evaluation, and its focus on practical applications and ethical considerations all contribute to its major achievements. The key contributions of the study on modeling and monitoring the SoH of Li-ion battery utilizing Random Forest Regression (RFR) with Artificial Neural Networks (ANN) include:

The suggested method provides a brand-new hybrid model that combines the pattern recognition capabilities of artificial neural networks (ANN) with the interpretability of random forest regression (RFR). The accuracy and reliability of SoH forecasts are improved by this combination.

The framework gathers and prepares a variety of battery statistics, such as voltage, current, temperature, cycling profiles, and battery volume. The models are trained and validated using a wide range of operational situations thanks to this vast dataset, increasing their adaptability.

The system's improvements in battery management benefit the field of battery technology and sustainable energy solutions as a whole and may hasten the adoption of Li-ion batteries in the transportation and renewable energy industries.

II. LITERATURE WORK

The sophisticated energy administration of autonomous electric cars has a big challenge with the online assessment of battery health. For online SoH assessment, ML-based techniques show promise. In this research, a ML-based approach for online Li-ion battery SoH estimate is proposed. A support vector machine is utilised in the technique to create a predictive diagnostic model. The charging records of new cells are used to create the support vectors that signify the inherent possessions of the Li-ion battery. While the support vectors have been discovered, the correlation coefficients associated with the SVMs for cells in various states of health are also detected. Matching partial charging curves to the saved SVMs is how the algorithm works. After comparing, a similarity factor is established to express the health of the data being evaluated. Fast on-board diagnostic of battery health is now possible since the system just needs partial charging curves, such as 15-minute charging curves. The anxiety about the driver's ability to charge the batteries accurately is relieved by the fact that partial charging curves can be derived from various voltage sections. Two commercially available Li-ion batteries were employed during the algorithm's train, validation, and test runs.These batteries had a $Li(NiCoMn)_{1/3}O_2$ cathode and a graphite anode. The findings indicate that in nearly all scenarios, the algorithm demonstrates high accuracy in predicting battery health, boasting an error rate lower than 2%. Due to the unpredictability of the driver's charging behavior, extending the voltage segment significantly may not always be feasible [11].

Lithium batteries must be maintained in excellent condition in order to guarantee the dependability and security of systems that store energy in batteries. Knowing exactly how well the battery is performing is very important for keeping everyone safe and reducing how much money is spent on maintenance. However, comprehending the specific physical and chemical alterations occurring during battery deterioration is not feasible. By utilizing the partial incremental capacity curve, the creation of the Gaussian process regression model becomes possible. First, we get the incremental capacity curves using a better method called the improved Gaussian filter approach. Health metrics obtained from the utilization curves provide the necessary information for the model. Moreover, the technique's average and variability are used to predict the uncertainty of the model and the battery's state of health, respectively. The suggested technique is used to show how well the degradation models work using four ageing datasets from NASA's data collection. Also, some situations where starting batteries are tested are used to show that the suggested method is strong and reliable. According to the findings, the proposed approach provides precise and consistent estimation of the health condition. Measuring the peak of the IC curves accurately can be challenging because disruptions often obstruct the highest point, making it difficult to observe [12].

In spite of the time-dependent and complex battery deterioration, Li-ion battery predictions and wellness oversight for electric automobiles are difficult. In order to estimate batteries SoH and anticipate Estimated Useful Life, the following paper suggests a model-data-fusion approach. A flexible and data-driven battery decline model is initially developed for modelling battery challenging loss behaviours, combining the metabolism grey model and multiple-output linear procedure regression analysis. Furthermore, a Particle Filter is employed to observe the decline in battery capacity, assess its overall condition, and make projections about its remaining usefulness. This filter helps eliminate any interference or errors in the charge data. Furthermore, tests are done to confirm that the suggested approach of combining model and data is correct. Precisely and dependably, the proposed technique accurately forecasts the remaining useful life and assesses the condition of an entity at various temperatures, as indicated by the validation outcomes. Accurately assessing the amount of power a battery can store is an impossible feat [13].

The internal temperature, state of health, and state of charge of batteries can all be effectively characterised using electrochemical impedance spectroscopy. Despite the necessity for ongoing history monitoring data, one might use the inherent connection among analogous component parts and resistance spectra's parts to predict the battery condition at a particular time. Any resistance-based battery administration system (BMS) design must start with recognising and evaluation of battery state-sensitive resistance factors. In order to detect and measure the level of reliance, a correlation study among comparable circuit components and resistance spectra of numerous commercialised Li-ion polymer cells at various SoH, SoC, and IT levels was carried out in this article. In order to identify the circuit components from the observed Impedance spectrum, curve fitting methods were applied to the observed Resistance spectra. The number of degrees of relationship among every resistance characteristic and the state value was measured using Pearson's r correlations matrix. This research then makes recommendations for appropriate resistance variables that have shown a strong correlation with SoC, SoH, and IT. A comprehensive understanding of the data is essential when creating models for battery management systems, enabling accurate real-time estimation of the battery's state. However, scientists discovered that certain wavelengths were used in the research [14].

The assessment of energy state of charge (SOC), that can both increase battery effectiveness and maintain the battery's secure efficiency, depends heavily on a precise forecast of the condition of health of Li-ion batteries. With longer charge and discharge cycles, the battery's capacity will decline whereas the resistance within it will rise and have an impact on how it is managed. An ageing test is used to examine the capacity attenuation features of Li-ion batteries. This method relies on the comparable circuit and online variable detection. Tests are used to confirm the model and method's viability and accuracy. The outcomes demonstrate that the method has excellent tracking and resolution. The largest SOC error during estimation is 2.03%, while the highest Ohmic impedance measurement error is 15.3%. It can provide guidance for the effective management of Li-ion batteries and improve the evaluation of the SOH and SOC of Li-ion batteries while reducing reliance on data from experiments. Nevertheless, the model's prediction value lags beyond the consequence as the batteries voltage varies dramatically at the end of the expulsion, increasing the prediction errors [15].

III. PROBLEM STATEMENT

The search for a definitive statement for Li-ion battery technology presents itself as a complicated and multifaceted task, which is supported by a thorough analysis of the body of existing literature. The modelling and monitoring of the SoH of Li-ion batteries are hampered by a number of ongoing problems, it becomes clear from a plethora of research. Since standard approaches frequently fail to capture the intricate and nonlinear interactions inherent in battery information, the battle to obtain exact and trustworthy SoH assessments is a common problem [16]. A fundamental barrier to integrating and harmonising various information for thorough modelling is introduced by the variety of data sources, which range from controlled laboratory trials to dynamic real-world applications. Advanced modelling methods are required because Li-ion battery behaviour is so complicated, yet there is always a risk that these techniques could overfit the data. Due to the strict requirements on speed and accuracy, real-time SoH monitoring, which is particularly important in dynamic environments like electric vehicles, continues to be a difficult endeavour. The literature emphasises the importance of ethical and safety issues, notably those relating to data privacy, security, and good battery management techniques. It is still difficult to bridge the gap between research models and actual implementation, particularly in fields like electric vehicles and renewable energy storage. These difficulties, coupled with a global shift towards green energy sources, highlight the urgent need for novel strategies that not only improve SoH monitoring precision and dependability but also complement the overarching objectives of green energy production and environmental protection.

IV. PROPOSED MECHANISM

In order to address the crucial demand for battery dependability and performance in applications ranging from EV to renewable energy systems, the proposed system focuses on the creation of a comprehensive solution for modelling and monitoring the SoH of Li-ion battery. To build a strong hybrid model, the system combines the advantages of (RFR) and Artificial Neural Networks (ANN). The system includes crucial elements like data gathering and preprocessing methods like Min-Max normalisation to guarantee data compatibility and consistency. With an emphasis on well-established measures, rigorous model training, optimisation, and performance evaluation will be carried out. Additionally, the approach is made to make it simple for the trained models to be seamlessly integrated into real-time battery management systems, providing continuous and precise SoH monitoring in useful, real-world settings. The system is being developed with the utmost ethical care and safety precautions, guaranteeing data protection, privacy, and prudent battery management. It is anticipated that this suggested system will lead to improvements in battery management dependability, increased practical applicability in crucial industries, and significant contributions to the field of battery technology and sustainable energy sources. The suggested RFR-ANN approach's workflow wass illustrated in Fig. 1.

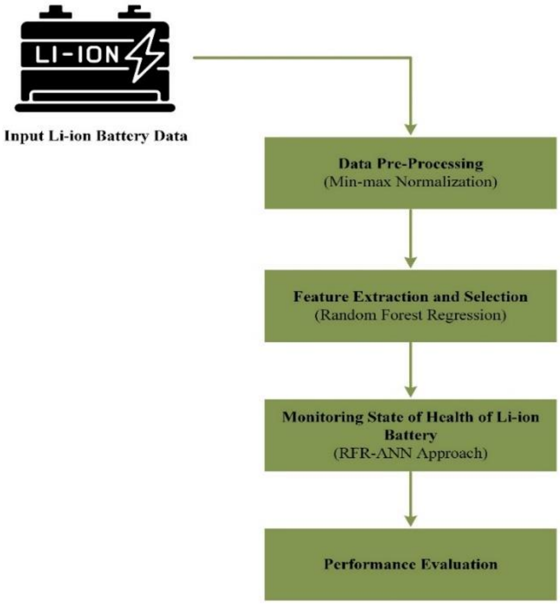

Figure. 1. Workflow of Suggested RFR-ANN Approach

A. Data Collection

The database was compiled from an online Kaggle dataset with a current and voltage accuracy of 0.1 percent of the entire scale. Two structures that correspond to the input and output anticipated to be acquired are generated in order to prepare the dataset so that TensorFlow can use it in the training phase. Filtering is done for the input data based on the following important dataset properties [17].

Table 1. Li-ion Battery Main Specifications.

Specification	Range
Chemistry	Li[NiMnCo]O2 (H-NMC) / Graphite + SiO
Nominal Voltage	3.6 Volt
Charge	1.5A,4.2,50mA End-Current (CC-CV) Normal 4A, 4.2V,100mA End-Current (CC-CV) Fast
Discharge	2V End Voltage, 20A MAX Continuous Current

B. Data Pre-processing

As a data scaling approach, min-max normalisation transforms numerical features that fall within a predetermined range, often between 0 and 1. It makes sure that every feature value is proportionally changed to fit the intended interval. Every point of data must first be subtracted from the minimum value of the feature before being divided by the range of the feature in the dataset (maximum value minus minimum value). This adjusts the feature values to a range between [0, 1], where 0 represents the dataset's least value and 1 represents its greatest value. To raise the level of efficiency of algorithms sensitive to feature scales, min-max normalisation is frequently employed in artificial intelligence and data preparation to make distinct features similar. The following is the formula for Min-Max normalisation of a feature 'Y' was expressed in Eqn. (1):

$$\hat{Y}_u = \frac{Y_u - min_s}{max_s - min_s} \tag{1}$$

These important features are converted into consistent scales employing Min-Max normalisation, making them suitable for modelling and improving the precision and efficacy of forecasting algorithms like RFR and ANN for determining and tracking the State of Health (SoH) of Li-ion batteries.

C. Retrieval and Selection of Characteristics Utilizing Random Forest Regression

Regression in machine learning is done utilising the supervised learning algorithm and bagging technique known as "random forest." In random forests, the trees grow in parallel, therefore there is no interaction between them as they develop. Based on the concepts of ensemble learning, Random Forest Regression uses a number of different decision trees to pool their collective knowledge in order to produce a more reliable and precise predictive model. This approach utilises a random subset of the information and characteristics to train every single decision tree in the random forest. The model is less likely to overfit to the quirks of the training data and is better prepared to generalise to new, unseen data by include this element of randomness during training. Once trained, the Random Forest's trees individually independently forecast the target variable. These predictions seem as real numbers when applied to regression issues. The Random Forest calculates an aggregate forecast for a given input by either averaging or taking the median of the individual tree predictions. The varied viewpoints of each tree are successfully combined through this averaging procedure, improving the model's ability to anticipate outcomes. The application of bootstrap aggregating, sometimes known as "bagging," is a crucial aspect of Random Forest. Individual decision trees are trained using this technique by repeatedly selecting small portions of the training data, frequently with replacement. The model becomes more robust and resistant to swings or outliers in the data by producing these varied training sets. The Random Forest is a powerful tool for regression applications because bagging helps to lower variance and improve overall performance. A random forest, which aggregates many decision trees with certain useful alterations, is a meta-estimator.

The State of Health of Li-ion battery is the target variable in this context, and feature extraction within the framework of Random Forest Regression (RFR) entails a methodical process of determining the relevance of individual variables in relation to the target variable. A dataset containing a variety of input features, including voltage, temperature, cycling profiles, and battery capacity (both charging and discharging), as well as related SoH values, is utilized to train the RFR technique initially. The influence on the representation's predictive performance when a certain feature is excluded from the dataset is then used to calculate significance ratings for each feature. Higher significance rankings are assigned to features whose removal significantly reduces prediction accuracy. The features are then sorted according to their relevance scores, with the most important features taking the top spots. For subsequent SoH predictions, a subset of these crucial traits can be selected based on the specific goals, potentially strengthening model effectiveness and interpretability while maintaining or enhancing forecast accuracy. The RFR model was reevaluated using the chosen feature subset, and the findings demonstrates that the model still exhibits good predictive efficiency with the smaller feature set. Additionally, this feature extraction approach helps to comprehend the main factors that influence Li-ion battery SoH and offers insightful information about the correlations that are present in the dataset, enabling rational decision-making and model interpretation.

D. Artificial Neural Network (ANN) Approach

A sophisticated data analysis technique called ANN uses generated neurons that are connected in a variety of ways to build a network. Additionally, neurons are referred to as the components that carry out the computation in an ANN model. As a result, they are connected and work together. The network created using ANN is essentially data-driven, that implies it trains straight from the information (for instance), and then computes and produces the output according to the input. The hidden layer sits among the inputs and outputs layers, which are essentially linked by neurons. Information are carried by every interaction. Fig. 2 shows an ANN structure.

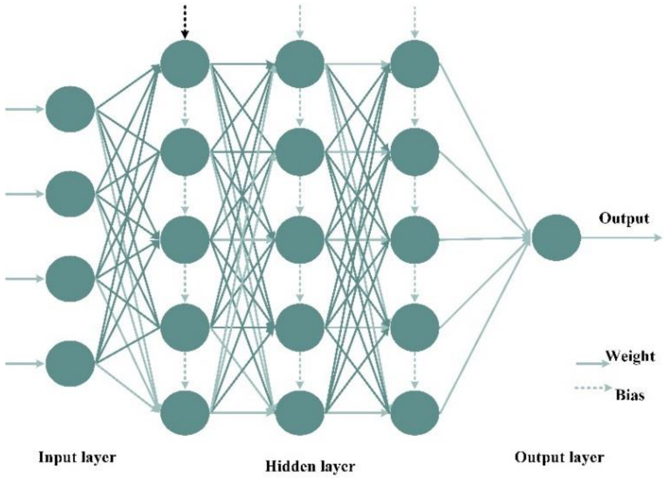

Figure. 2. Schematic of ANN

A transfer function, often termed as an activation function depending on quadratic equations, is employed to map inputs vertices to output units in a specific way. It is created by combining the resulting products and the extrinsic biases. Any connection among vertices in one layers and vertices in the subsequent is given a value. It displays how strongly the origin nodes effects each nodes it is attached to and might have a positive or negative ratio. The very next stage is to give every nodes in the subsequent stage a bias number, that could be either negative or positive. The grade of that nodes increases as a result. The selection of biases and weights could be randomized or intentional. Activation functions apply nonlinear changes to incoming signal (transfer functions). The modified outputs acts as the inputs for the subsequent level of neurons. While sigmoid Equation in 2 is the transferring activation function which is most frequently employed, Among the various activation functions utilized in machine learning, linear, sigmoid, and hyperbolic tangent are frequently utilised. The activating function's objective is to add non-linearity to a neuron's response [18].

$$f(y) = \frac{1}{1+e^{-y}} \qquad (2)$$

Equations (2) and (3) can be used to numerically characterize a neurons, where y1,y2………ym are the receiving signals; wk1wk2……..wkm are the neuron's synapses impulses k; l_k is a linear composite of the incoming signals' outputs.; b_k is the biasing factor; ∅ is the activation function; and represents the neuron's final output.

$$l_k = \sum_{j=1}^{n} Sw_{ki}y_i \qquad (3)$$

$$x_k = \emptyset(l_k + b_k) \qquad (4)$$

The ANN procedure includes all three phases of learning, assessment, and validating. The back propagation strategy is among the more popular because there are several techniques accessible for building architectures of neural networks. The related parameters are changed in this procedure to allow the neural network to continuously learn. Even though the LM is the most effective and reliable method, operating the data requires additional random access memory (RAM). The LM technique is employed to develop the ANN due to its speedy divergence and reliability [19] . The ANN is simplified by a few presumptions, such as the fact that it ignores the physiological meaning of the parameters and assumes the information as non-dimensional. Given a lack of information to prepare the model, ANNs could indeed be utilised to forecast infrequent or catastrophic events [20]. The ability of ANN to establish an objective association among independent and dependent parameters is just one of their distinctive characteristics. Additionally, the link among the dependence and independence factors could be determined without making any assumptions regarding any numerical expression of the phenomenon. ANN models, as with any strategies, offer benefits and drawbacks. An important benefit of ANNs is their autonomous resolution of relationships among parameters even without requirement for previous hypotheses regarding the origin of these associations. The two main downsides of ANNs are their propensity to overload the information utilized to develop them and its insufficient transparency in contrast to other quantitative methodology. Technology reliance, uncertain networks lifetime, determining the proper framework, and unexplainable networks behaviour are the key obstacles to applying ANN for addressing non-linear and complicated issues.

Artificial Neural Networks (ANN) are an essential tool that could be utilised to evaluate the State of Health (SoH) of Li-ion battery and make predictions with greater accuracy. A precise evaluation of battery health is crucial since Li-ion batteries are essential to the operation of many different technologies, including electric vehicles and renewable energy storage systems. In this setting, ANN shows itself as a powerful tool capable of identifying complex relationships and patterns in the battery data, allowing accurate SoH predictions. Beginning with a thorough gathering and pretreatment of battery-related data, ANN modelling is ensured as well as the data's quality. The ANN is then subjected to rigorous training and validation, assisted by well-defined performance metrics that evaluate its predictive accuracy. The evaluation of the model includes a critical assessment of how well it performs in comparison to industry standards or alternative predictive methodologies. The ANN model is fine-tuned to improve its predicting ability, and hyperparameter tuning and optimisation are carried out. Additionally, deciphering the predictions made by the ANN and visualising the patterns that were learned offer insights into the variables affecting the health of Li-ion batteries. ANN-based models make a substantial contribution to battery management by producing precise SoH forecasts, enabling informed decisions, and enhancing the performance and sustainability of battery-dependent systems. In terms of future research, the incorporation of real-time data and the investigation of ANN applications in large-scale battery systems offer promising avenues, highlighting the ongoing significance of this topic in the hunt for dependable, sustainable energy solutions.

E. RFR-ANN Framework for Monitoring the SoH of Li-ion Battery

A cutting-edge method for addressing the urgent demand for accurate and immediate battery health evaluation in various applications is the RFR-ANN framework for monitoring the SoH of Li-ion Batteries. This hybrid framework's central component smoothly combines the two potent methodologies Random Forest Regression (RFR) and Artificial Neural Networks (ANN). The RFR component brings to the table its ensemble learning capabilities and excels at identifying salient characteristics and nonlinear correlations within battery data. The ANN component, on the other hand, makes the most of its ability to understand intricate patterns and correlations, making it the perfect collaborator in this hybrid research. For the best model performance, data collection and preparation make sure that the input data, which includes important battery characteristics like voltage, temperature, cycling profiles, and capacity, is cleaned, normalised, and feature-rich. The core of the framework is model training and optimisation, where RFR and ANN parts are tweaked to cooperate and produce reliable SoH predictions. The model's predicted accuracy is scrutinised employing performance evaluation metrics. This framework stands out for its real-time integration capability into battery management systems, which enables continuous SoH monitoring in dynamic operational settings—a vital feature for applications like electric vehicles and renewable energy storage. Data privacy, security, and ethical battery management practises are all upheld, and ethical considerations are not disregarded. The framework's effectiveness is attested to by real-world case studies and findings, which indicate enhanced battery dependability and performance. Looking ahead, this paradigm shows potential for more research, including the improvement of model robustness and adaptability. The RFR-ANN framework ultimately serves as a beacon in the quest for accurate SoH monitoring, making a substantial contribution to battery management techniques and the more general objectives of sustainable energy solutions.

V. RESULT & DISCUSSION

In order to monitor the SoH of Li-ion Batteries, the study developed a hybrid RFR-ANN framework. A variety of performance metrics, such as provide a quantitative evaluation of the framework's efficiency and highlight its predictive accuracy. The performance of the model across multiple battery datasets may be clearly understood with the help of visual aids like tables and graphs, which highlight trends and patterns in the data.

A. Discharge Capacity Vs Temperature at different Celsius Rate

In order to fully understand the behaviour of Li-ion batteries, this study will examine the link between discharge capacity and temperature at various C-rates (0.05C, 0.5C, 1C, and 2C). To determine a battery's temperature sensitivity, the discharge capacity, a crucial statistic that reflects the battery's ability to supply energy, is tested across a range of temperatures. C-rates, which stand for the rate at which a battery is charged or drained in relation to its volume, are also taken into account. Through meticulous experimentation, it gather data that illustrates how discharge capacity reacts to temperature changes at various discharge rates. The findings provide light on critical elements affecting battery performance and reveal the complex interplay between temperature, C-rate, and discharge capacity. This has ramifications for everything from electric vehicles to portable gadgets to renewable energy storage. Fig. 3 depicts the Discharge Capacity vs. Temperature at Various Celsius Rates.

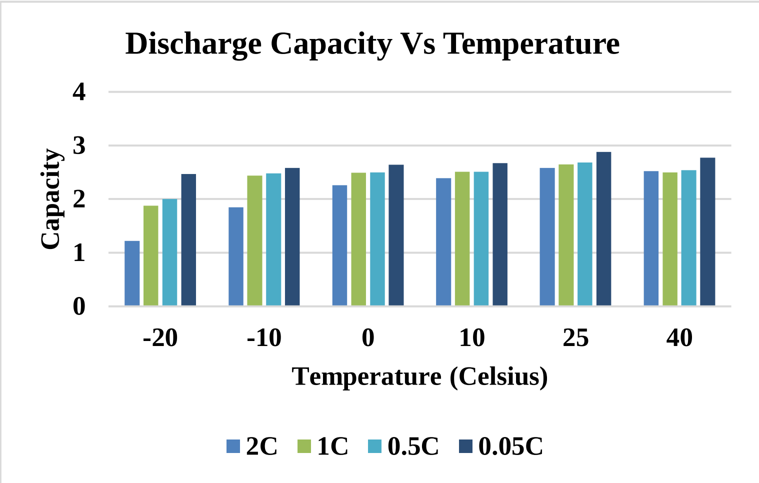

Figure. 3. Discharge Capacity Vs Temperature

B. Open Circuit Voltage vs Temperature

The dynamic link between Open Circuit Voltage (OCV) and temperature is examined in this work for Li-ion batteries throughout a temperature range of -20°C to 40°C, elucidating the temperature sensitivity of this crucial battery parameter. OCV, which measures a battery's internal electrochemical condition and state of charge when it is not being used, has a big impact on the health and functionality of the battery. We demonstrate how OCV values change in response to temperature changes by careful experimentation and data gathering, identifying both expected patterns and surprising variances. For battery management systems, electric vehicle performance optimisation, and renewable energy storage, understanding this temperature-dependent OCV behaviour is essential because it helps develop strategies for maintaining battery health and efficiency under various environmental conditions, ultimately advancing sustainable energy solutions. Fig. 4 displays the temperature-dependent open circuit voltage of the lithium-ion battery.

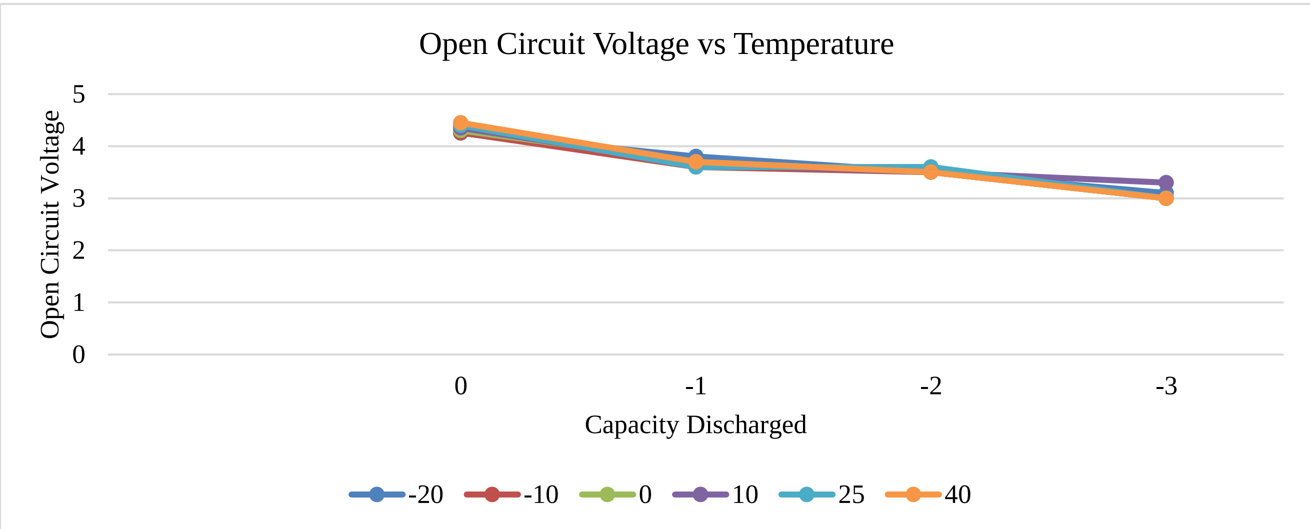

Figure. 4. Temperature-dependent OCV of the lithium-ion battery

C. Discharge Resistance versus Temperature

This study explores the relationship between temperature and discharge resistance for a Li-ion battery, looking at how changes in temperature affect this important parameter. An essential characteristic of battery behaviour that affects performance and efficiency is discharge resistance. The experimental data is presented together with discharge resistance measurements for a temperature range of -20 °C to 40 °C. Intriguing conclusions could be drawn from the data analysis, such as the fact that discharge resistance tends to rise as temperature falls. This pattern is consistent with the battery's reduced ion mobility at lower temperatures, which obstructs current flow and raises resistance. In contrast, discharge resistance falls as temperature rises, indicating better ion mobility and less resistance to current flow. These findings have important ramifications for battery performance in many climatic situations, such as cold-weather electric vehicle operation or temperature-sensitive renewable energy storage systems. To progress the development of sustainable energy solutions, it is essential to comprehend the temperature-dependent behaviour of discharge resistance in order to maximise battery efficiency and ensure dependable performance in a variety of real-world applications.

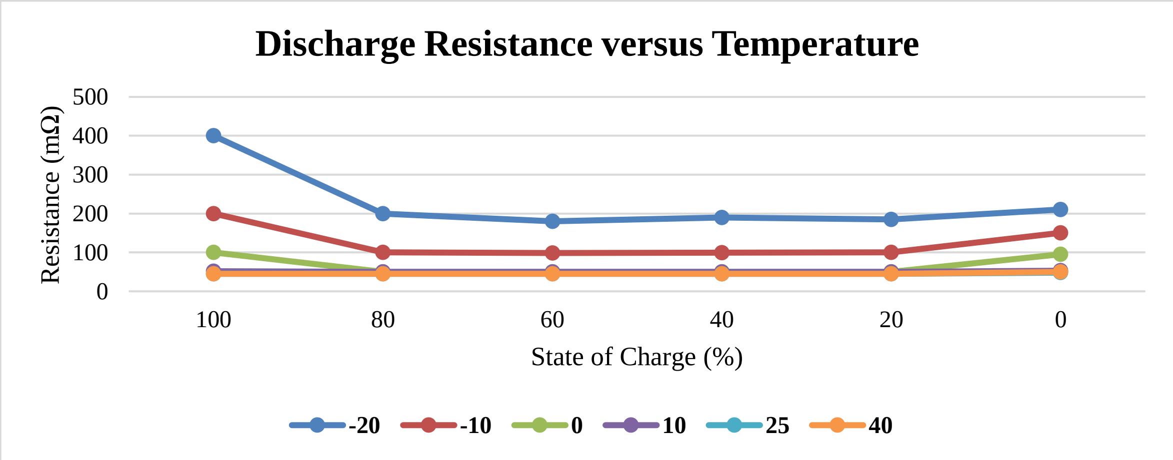

Figure. 5. Discharge Resistance versus Temperature

D. Performance Assessment of the suggested Approach

The error performance metrics commonly selected to assess the accuracy of a forecasting framework include Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared. The expressions for computing these metrics are outlined in equations (5) to (8):

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \quad (5)$$

$$MSE = \frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2 \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \quad (7)$$

$$R^2 = 1 - \frac{\sum_{j=1}^{N}(u_j - \grave{u}_j)^2 / N}{\sum_{j=1}^{N}(\breve{u}_j - r\grave{u}_j)^2 / N} \quad (8)$$

Where the actual rate is u_j and the prediction accuracy is u ̀j and u ̆_j represents the mean amount. R2's set of values is (0, 1). The prediction reliability increases as MAE and RMSE values get nearer to R - square, as does the difference among the anticipated value and the exact range. The approach fits the data more accurately the nearer R - square would be to one. The Errors Prediction Models for SoH of Li-ion Battery are displayed in Table 2.

A key component of this research is the evaluation of predictive models for tracking the SoH of Li-ion batteries employing a variety of methodologies. The novel Random Forest Regression with ANN (RFR-ANN) hybrid model proposed herein has been thoroughly examined using four key performance metrics: MSE, MAE, RMSE, and R-squared. These four prominent methodologies, namely Artificial Neural Networks, Regression Methods, SVM, and the novel have all been subject to extensive scrutiny. The RFR-ANN framework stands out among the competitors, displaying the lowest MSE (0.20), MAE (1.65), and RMSE (1.23) values, demonstrating its unmatched accuracy in forecasting battery SoH. With an R2 coefficient of 1.0078, which denotes a nearly perfect fit between predicted and actual data, this extraordinary precision is further supported. With a competitive MSE of 1.00, MAE of 5.54, RMSE of 10.22, and an R2 of 0.9234, the Regression Method comes in close second and displays commendable performance. With an MSE of 3.89, MAE of 13.56, RMSE of 20.29, and an R2 of 0.9608, SVM exhibits good results but displays somewhat higher error rates.

Table 2. Errors prediction models for SoH of Li-ion Battery.

Techniques	MSE	MAE	$RMSE$	R^2
ANN	1.05	6.77	12.55	0.9778
Regression Method	1.00	5.54	10.22	0.9234
SVM	3.89	13.56	20.29	0.9608
RFR-ANN (proposed)	0.20	1.65	1.23	1.0078

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The RFR-ANN hybrid approach's superiority is demonstrated by its extraordinary accuracy as well as by how it has the ability to revolutionise Li-ion battery SoH monitoring and open up new possibilities for improved battery management and sustainable energy sources. Fig. 6 depicts the performance evaluation of the proposed approach.

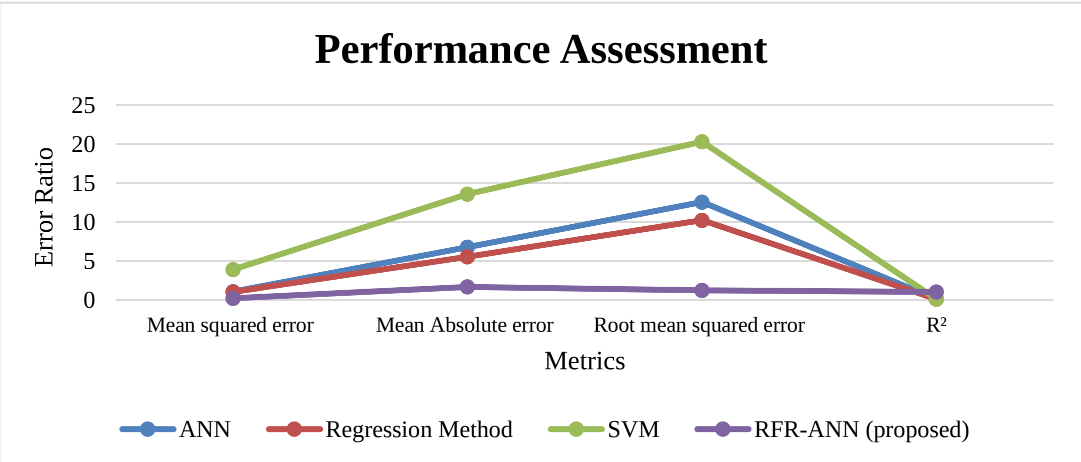

Figure 6. Performance Assessment of the suggested Approach

VI. CONCLUSION

This study has investigated a synergistic method that combines the strengths of RFR-ANN in the quest of modelling and monitoring the SoH of Li-ion battery. It constructed a solid dataset that is ready for analysis by fusing data from many sources to provide comprehensive data covering voltage, temperature, cycling patterns, and battery capacity (charging and discharging). The methods taken during data preprocessing, such as Min-Max normalisation, have ensured consistent scales among pertinent features, improving the data's suitability for modelling. The study's models, which include standalone RFR, ANN, and hybrid RFR-ANN models, provide encouraging findings in terms of forecasting battery SoH. Accurate SoH evaluations have been obtained by thorough training, optimisation, and evaluation, with performance indicators including root mean square error, mean absolute error and R-squared demonstrating the effectiveness of the models. In particular, the hybrid RFR-ANN model demonstrates the benefits of combining interpretability with complexity, providing improved predictive accuracy. Additionally, the integration of these models into real-time SoH monitoring systems has the potential to revolutionise battery management across a range of industries, including renewable energy installations and electric vehicle manufacturing. It is crucial to remember that ethical and safety concerns, such as data privacy and proper battery management, continue to be of the utmost importance. The outcome of this research highlight the position of combining several modelling approaches to produce reliable Li-ion battery SoH monitoring solutions. The combination of conventional ML and DL techniques has the potential to increase battery performance, reliability, and safety as the sector develops, paving the way for a future powered by renewable energy sources. To further improve battery health monitoring, future study should include scalability, real-world application, and upcoming technologies.

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