Journal of Advances in Management, Engineering and Science (JAMES), July 2026; 1(3): 37-46

Research Article

Group Learning Algorithm-Guided Hybrid Learning Framework for Battery Degradation and Lifetime Prediction in Electric Vehicles

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Received: 16th May 2026; Accepted: 28nd June 2026; Published: 16th July 2026

https://doi.org/10.65470/james.v1i03.35

Abstract – *Accurate forecast of battery deterioration and lifetime is essential for the reliability, safety and efficiency of EV. Lithium-ion batteries can age, but if you understand how they age, you can manage them better and make them last longer. Battery degradation is affected by factors such as the number of cycles, depth of discharge, charge/discharge rates, temperature and electrochemical processes. This work presents a GRLA-ConvBiLST Hybrid Learning Framework for accurate prediction of battery deterioration and lifetime. Firstly, CEEMDAN decomposes battery capacity data into high and low frequency components. Then, the battery degradation patterns are characterised by health-related measures such as DC (dI/dV), DV (dV/dQ) and ICA (dQ/dV). The ConvBiLST network captures the spatial and temporal dependencies and then the network hyper-parameters are optimised by the GLA for better learning efficiency and prediction accuracy. The experimental findings reveal that the proposed framework achieves the best State-of-Health (SOH) prediction accuracy of 94.12%, outperforming CNN, LSTM, CNN-LSTM and GRU models. The results show that the suggested approach can efficiently and reliably solve the problems of EV battery deterioration and lifespan prediction, which supports the intelligent battery management systems, extends the service life of batteries and enhances the performance and sustainability of EV.*

Keywords— *Lithium-ion Batteries (LIB), Electrical Vehicle (EV), Renewable Energy Storage (RES), Group Learning Algorithm (GLA), Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Incremental Capacity Analysis (ICA), Differential Voltage (DV), Differential Current (DC).*

INTRODUCTION

With the world's automotive industry facing formidable obstacles from climate change, pollutant emissions, and energy scarcity, the creation of electric vehicles (EVs) is being more and more seen as crucial to achieving a carbon-neutral transportation vision and easing the transition to a low-carbon economy. The battery pack is an integral part of electric vehicles and has a major impact on the vehicle's performance and safety. Nevertheless, as time passes, the battery's capacity decreases and its internal resistance increases; this is a natural consequence of electrochemical systems. Thus, for service life evaluation, predictive maintenance, and second-life utilisation, it is necessary to precisely quantify the degree of ageing in batteries and predict additional degradation trends, particularly under highly dynamic and unpredictable operating situations [1]. An essential part of building the infrastructure for electric transportation systems is creating and improving emission-free electrochemical energy storage devices and ways to monitor and optimise their performance. Rising carbon emissions, the climatic change they cause, and energy shortages are addressed by centralised and decentralised energy storage, as well as the dynamic growth of new technologies. Because of their extended cycle life, low self-discharge rate, and high power densities, lithium-ion batteries (LIBs) have emerged as a leading option among energy storage solutions. This has opened up new possibilities for the EV industry and facilitated the widespread adoption of portable electronic devices [2].

EV and Renewable Energy Storage (RES) rely heavily on battery technology, which has come a long way in the past few decades. Innovations in LIB have garnered a lot of interest because of their great performance, little maintenance requirements, and high energy density. Also, for the sake of future EV performance, evaluating LIBs for dependability and safety is a major concern. The longevity of the batteries is a major drawback of LIBs since it affects both the amount of energy provided and used in LIB-related applications [3]. Among the many applications made possible by the LIB in the modern era of low-carbon technology are new energy vehicles and the regulation of renewable power sources like solar and wind. The technology's relatively high price, short lifespan, and insufficient energy density are still obstacles to its widespread use. Optimal battery capacity is a special challenge due to the strong relationship between LIB lifetime and operational factors including temperature, charge, and operational state-of-charge range. It is the state of the batteries and how long they last that determines their total efficiency. Computer vision and the deep learning (DL) method are examples of intelligent and flexible AI that might be used to predict the batteries' health and lifespan [4].

The following is the structure of the work. Models such as GLA, CNN, and LSTM are detailed in Section 2, which also covers the work approach. The suggested GRLA-ConvBiLST Model, as well as the BiLSTM and GLA-BiLSTM models, are described in Section 3. Also included is a description of the experimental setup. The results and discussions are presented in Section 4. The job is finally concluded in section 5.

RELATED WORKS

Developed a new model for predicting LIBs, the BL-ELM, and introduced the Gradient Boosting Regression Tree to estimate battery cycle life. While it investigated the potential of RNNs, they proved that CNNs were effective in the deep learning field [5]. For residual usable life (RUL) prediction, researchers have also investigated hybrid approaches including VMD with particle filters (PF), GPR with LSTM, and Broad Learning Systems (BLS) with VMD [6]. While these hybrid systems strive to enhance prediction accuracy by combining various methodologies, they frequently encounter difficulties stemming from computational complexity [7]. In order to forecast RUL and the associated uncertainty, it used raw data acquired within 500–10,000 s and trained a temporal convolutional neural network (CNN) on the battery's current, voltage, and temperature [8].

In order to forecast the RUL, trajectory prediction algorithms use the capacity degradation trajectory all the way to the end of life (EOL) [9]. Most of the time, a capacity trajectory model will be used to accomplish this [10]. To forecast how long a battery will last, a simple mathematical function like the linear, polynomial, or exponential function can be used as a trajectory model [11]. Additionally, certain recursive models, such as the ARIMA model, GPR model, LSTM-RNN, etc., can be used as trajectory models by treating the degradation trajectory of capacity as a time series [12]. DT, MLP, RF, RNN, LSTM, and Dual-LSTM are among the models that have been used to predict the RUL of batteries [13].

A new method that aims to improve the accuracy and reliability of battery life predictions is the Denoising Transformer-based Neural Network (DTNN) [14]. The DTNN takes advantage of the Transformer's capacity to detect input sequence correlations over extended periods of time, setting it apart from conventional models [15]. Later on, the SOH is predicted using these characteristics as inputs to the BiLSTM network[16]. The method offers better prediction accuracy when compared to other neural networks[17]. A literature review found that IALO-SVR, an improved Ant Lion Optimiser algorithm and Support Vector Regression, was the most effective approach for estimating SOH [18]. By optimising the SVR kernel parameters with the IALO algorithm, this technique improves the accuracy of SOH prediction [19].

This work's key contributions are outlined below.

- To take advantage of both CNN and BiLSTM's strengths, a new hybrid architecture is suggested. In order to comprehend the structural properties of the input data, this integrated model makes use of CNN to efficiently extract spatial features from the data. Using both historical and real-time data, the model is able to track and forecast the SoC of the battery using BiLSTM, which capture temporal dependencies. This synergy enhances the accuracy and efficiency of SoC estimations, making it a robust tool for managing the performance and longevity of Li-ion batteries in EVs.
- A state-of-the-art method that improves model training by quickly locating the ideal configuration settings, the GRLA is used to fine-tune the CNN-BiLSTM network's hyperparameters. By optimising the learning process using principles of evolutionary computation and group dynamics, GRLA greatly improves the model's predictability and stability. This approach improves the model's flexibility to different operating conditions and speeds up convergence.
- A thorough evaluation of the suggested GRLA-ConcBiLST model's performance is carried out in comparison to two other models: one that is based on GLA and the other that is based on CNN. When compared to utilising just one model, this study shows that combining CNNs and BiLSTM has both individual and combined benefits. The evaluation provides a transparent and empirical basis for the model's efficacy by carefully assessing and demonstrating the improved capabilities of the hybrid model in real-world settings using numerous metrics.

METHODLOGY

A novel approach to predicting the degradation of LIB is put forth, one that is grounded in theoretical models of fracture propagation. As a result, stress factors like depth of discharge have an exponential effect on the ageing process. To account for hybrid car or vehicle-to-grid operations, a stress metric is developed from arbitrary charge and discharge histories.

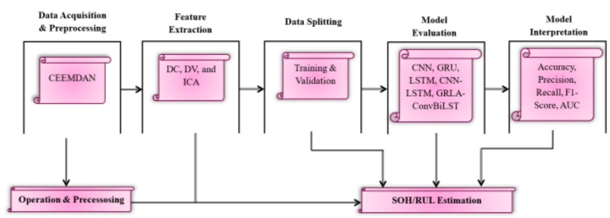

Fig. 1. Overview of the Proposed Model

Each step of the five-step pipeline is depicted in Figure 1. The first step is data acquisition and preprocessing. The second step is feature engineering using differential analyses. The third step is building a hybrid GRLA-ConvBiLST model. The fourth step is training and validation. The last step is evaluation and interpretation.

The suggested hybrid optimisation system was tested and fine-tuned with open-access datasets that record real-world EV charging patterns, traffic patterns, and renewable energy variability across a range of operational scenarios [20]. This dataset allows for precise modelling of unpredictable EV arrival patterns and charging-demand uncertainty; it includes time-stamped records of EV charging sessions, which include charging power, arrival and departure times, charging duration, initial and target state-of-charge (SoC), and energy consumption. Several thousand EV charging sessions from various sites make up the dataset, which covers several months of operation. The charge data cover time intervals ranging from minutes to sub-hourly gaps, allowing for detailed examination of both short-term charging dynamics and longer-term demand trends. Including both peak and off-peak times, as well as weekdays and weekends, the data captures genuine fluctuations in infrastructure utilisation and congestion levels.

A. Data Preprocessing:

1) CEEMDAN:

The CEEMDAN is an enhanced EEMD variant. When applied to non-stationary or non-linear signals, the CEEMDAN reduces them to a collection of intrinsic mode functions, improving both the signal-to-noise ratio and degradation accuracy [21]. Incorporating adaptive noise handling, the CEEMDAN expands upon the EEMD's foundation. With its enhanced anti-pattern mixing performance, it solves the problems of EEMD's incomplete decomposition and large reconstruction imperfections. Here are the steps to execute the CEEMDAN:

1. Equation (1) shows how to create a new capacity sequence by adding Gaussian white noise $\varepsilon_0 \omega_j(s)$ with an initial amplitude ε_0 to the original battery capacity sequence $D(s)$. The number of battery cycles is denoted by t in this context.
$$D_j(s) = \varepsilon_0 \omega_j(s) + D(s) \quad (1)$$
2. An iterative process of decomposing $D_j(s)$ using EMD yields a set of intrinsic mode functions IMF_t . Equation (2) shows that the first mode component IMF_1 of the battery decomposition is obtained by taking the overall average of these functions.
$$IMF_1 = \frac{1}{J}\sum_{j=1}^{J} IMF_1^j \quad (2)$$
3. Decompose the battery and find the first unique residual signal using Equation (3).
$$Q_1(s) = D(s) - IMF_1 \quad (3)$$
4. In the context of EMD processing, F_l represents the l^{th} mode component. Equations (4) and (5) express the decomposition of the signal $Q_q(s) + \varepsilon_1 F_1\left(\omega_{(j)}(s)\right)$ into the second mode component and the second residual signal, respectively, via each experiment.
$$IMF_2 = \frac{1}{J}\sum_{j=1}^{J} F_1\left(Q_1(s) + \varepsilon_1 F_1\left(\omega_{(j)}(s)\right)\right) \quad (4)$$
$$Q_2(s) = Q_1(s) - IMF_2 \quad (5)$$
5. For the l^{th} step, use Equation (6) to calculate the $(l+1)$-th mode component, and repeat Step (4) to continue decomposing the signal.

$$IMF_{l+1} = \frac{1}{J}\sum_{j=1}^{J} F_1\left(Q_l(s) + \varepsilon_l F_l\left(\omega_{(j)}(s)\right)\right) \quad (5)$$

6. Keep doing Step 5 until further decomposition of the residual signal is impossible. The total number of mode components produced thus far is l . Equation (7) expresses the original signal once decomposition finishes.

$$D(s) = Q(s) + \sum_{l=1}^{L} IMF_l \quad (6)$$

B. Feature Extraction:

1) Incremental and Differential Analysis:

Figure 2 shows the process of extracting features from raw cycling data across multiple domains; this involves normalising the voltage capacity curve into three diagnostic indicators: The formulas for Incremental Capacity Analysis (ICA), Differential Voltage (DV), and Differential Current (DC) are ICA multiplied by (dQ/dV), DV multiplied by (dV/dQ), and DC multiplied by (dI/dV), respectively. For the sake of clarity, there are the explicit mathematical versions of the shorthand terms (ICA, DV, DC) throughout the manuscript. During cycling, variations in internal resistance, lithium inventory, and active material availability are reflected in the amplitudes and positions of the peaks across these graphs, which show electrochemical deterioration.

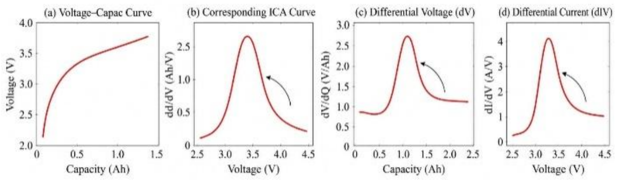

Fig. 2: Illustration of Feature Extraction: a) Voltage Capacity Curve b) ICA (dQ/dV) c) DV (dV/dQ) and d) DC (dI/dV)

Batteries can only be diagnosed with any degree of accuracy and clarity if sensitive electrochemical markers reflecting internal degradation dynamics are used. Voltage (V), current (I), and capacity (Q) interplayed throughout charge-discharge operations were captured by computing three differential transformations from the preprocessed cycling data. Equation (8) defines DV, which measures the voltage's reaction to an incremental charge.

$$DV \equiv \frac{dV}{dQ} = \frac{U_{j+1} - U_i}{R_{j+1} - R_j} \quad (8)$$

Thus, an imbalance between the electrodes or an increase in polarization/internal resistance are indicated by a widening or shifting of the DV peaks. The relationship between voltage and current is defined by Differential Current (DC) as Equation (9).

$$DC \equiv \frac{dI}{dV} = \frac{J_{j+1} - J_i}{U_{j+1} - U_j} \quad (9)$$

called ohmic losses, polarisation effects, and reaction kinetics, which are highlighted by the current oscillations. As illustrated in equation (10) , Incremental Capacity Analysis (ICA) quantifies the capacity variation in relation to voltage.

$$ICA \equiv \frac{dQ}{dV} = \frac{R_{j+1} - R_i}{U_{j+1} - U_j} \quad (10)$$

As a result of lithium inventory loss, active material depletion, SEI growth, and amplitude attenuation, it is extensively utilised to monitor ageing. Degradation is usually seen in practical diagnostics as ICA peaks moving to the right, towards higher voltages, and with smaller peak magnitudes. The three electrochemical domains' degradation signatures could be learned simultaneously by stacking the ICA, DV, and DC curves into a single three-channel tensor, which allowed the convolutional front end of the suggested network to engage in cross-domain learning.

C. Model Training:

1) Model BiLSTM and Hyperparameter:

Since the LSTM design is limited to capturing only positive dependencies, it runs the risk of missing out on important information when using the long-term gated memory [22]. The BiLSTM neural network, which can handle both forward and backward flow of input, was developed by researchers to address this limitation. These concealed sequences are fed into the output layer, where they are combined. Equations (11) and (12) are used by BiLSTM to improve the output sequence using forward and backward sequences.

$$\vec{g}_s = e_{lstm}(w_s, \vec{g}_{s-1}) \quad (11)$$

$$\overleftarrow{g}_s = e_{lstm}(w_s, \overleftarrow{g}_{s+1}) \quad (12)$$

$\vec{g}_s$ and $\overleftarrow{g}_s$ stand for the forward and reverse cell states at time s, respectively. The input to the LSTM cell at time s is represented by w_s, while the prior and subsequent states of the cell are shown by $\vec{g}_{s-1}, \overleftarrow{g}_{s+1}$. Equation (13), where x_z and a_z represent the weight and bias matrices, shows that the final output z_s is generated after two LSTM layers process the input data w_s. This is achieved by concatenating the outputs of the two layers.

$$z_s = x_z\vec{g}_s + x_z\overleftarrow{g}_s + a_z \quad (13)$$

A new difficulty has emerged: finding the ideal parameters of BiLSTM such that the network model structure is aligned with the input data, training speed is enhanced, and overall network performance is boosted. BILSTM model hyperparameters include learning rate, LSTM unit count, bidirectional layer count, and iteration count. It could be challenging to gather all the necessary information for the samples' training if the quantity of LSTM units and bidirectional layers is insufficient. Overfitting can occur if the sample size is excessively large. The iterations count indicates how many times the network processes the training data. The model might not converge if this value is too tiny, but it might be too slow if it's too big. In optimisation, the size of the step is determined by the learning rate. When the learning rate is too high, the ideal value is overshot, and when it's too low, convergence is sluggish.

2) GLA based tuning of BiLST:

Changing a number of hyperparameters is a common way to evaluate the efficacy of existing data-driven methods for SoC estimation. On the other hand, getting good results using this method may be a real pain in the neck and takes a lot of time and work. An alternate approach to this problem could be to develop a smarter SOC estimating algorithm that takes into account a variety of operational situations when calculating SoC. One effective method is to create a smart hybridised optimisation strategy by merging data-driven algorithms with heuristic optimisation techniques. Improving the hyperparameters to obtain the minimised value of the objective function while checking all constraints might be used to create this optimised data driven system of circuit (SoC) estimate. It is challenging to traverse the vast and intricate hyperparameter space of BiLSTM. Thus, to acquire hyperparameters that work effectively, a very efficient GLA technique can be employed. The iterations, learning rate, number of LSTM units and bidirectional layer count, make up the BiLSTM model's parameters. Here is the set of parameters and their range of values: learning rate (lr) is between 0.0001 and 0.1, Ns is between 5 and 50, Bn is between 3 and 30, and it is between 50 and 500.

3) GRLA-ConvBiLST Model for SoC Estimation:

Consideration of both geographical and temporal features is necessary for an appropriate estimation of battery SoC. Both spatial and temporal aspects are important; the former refers to the connections between the inputs at the moment, while the latter highlights the connections between the current state of the system and inputs from the past. They suggest a CNN-BiLSTM network hybrid to handle spatial and temporal variables for robust and generally accurate SoC estimation, which might help with this difficulty. The original data contains advanced spatial information, which may be extracted using CNN. The current SoC and historical inputs can be modelled using LSTM. An essential function of the 1D layers of convolution is to extract features from the data that may be sent into the LSTM layer.

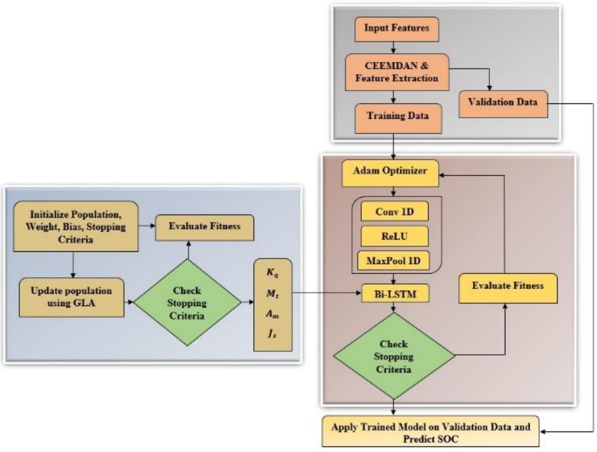

Fig 3: Flowchart for GRLA-ConvBiLST

To enhance the network's performance, one can tweak the convolution kernel's weight and the window's width to extract multiple data features. In contrast to CNN, which limits the network to considering only the associations between the current inputs, LSTM takes into account the correlations between the current and previous inputs. In order to train the deep neural network, it employs the MSE loss function. Using the MSE in Equation (14), the total loss function is computed at the conclusion of every forward pass during training.

$$cost = \frac{\sum_{s=1}^{n}\left(SOC_{ref.s} - SOC_{mea}, s\right)^2}{m} \quad (14)$$

the output of the proposed network at time s is represented by SOC_{mea}, s, and $SOC_{ref.s}$ is the genuine SoC value. Fig. 3 displays the GRLA-ConvBiLST model that has been suggested.

RESULT AND DISCUSSION

One crucial feature of LIB is its use in electric vehicles and consumer devices. Nevertheless, because of the influence of operational and environmental factors, it is challenging to forecast their lifespan performance. In order to ensure optimal performance throughout the lifetime of an energy management system, SOH and remaining-useful-life (RUL) estimates have become essential components. Evaluating SOH and RUL has thus become an important academic and commercial research problem because of the non-linear behaviour of electric car battery health prediction.

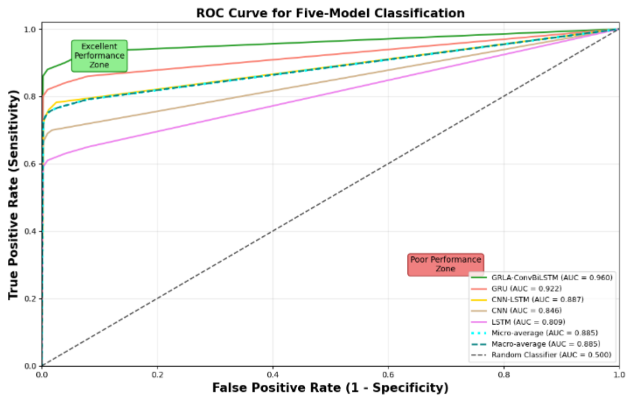

Fig 4. ROC Curve for Five Models

The discriminative abilities ROC curve and area under the curve are shown in Fig. 4. A large AUC indicates that the model is likely to be able to differentiate between EV battery degradation and lifetime prediction. Furthermore, the ROC curve shape indicated that the model appropriately balances specificity and sensitivity (recall) across various thresholds, which is crucial for datasets that are imbalanced.

TABLE I. DIFFERENT MODEL METRIC COMPARISON

Models	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**

LSTM	78.21	76.54	74.09	78.91	80.45
CNN	82.33	80.03	78.82	82.89	84.62
CNN-LSTM	86.48	84.56	82.60	86.79	88.70
GRU	90.63	88.72	86.45	90.92	92.24
GRLA-ConvBiLST	94.12	92.25	90.30	94.80	96.02

Table 1 shows the results of our comparison of the proposed GRLA-ConvBiLST model to alternative methods for predicting the lifetime of electric vehicle batteries and understanding battery degradation. Using a number of important performance indicators, they assessed each model's capacity to make accurate predictions. Accuracy, precision, recall, and the F1-score—a compromise between the two—were all part of it. The AUC was also considered; it shows how effectively a model can differentiate across categories. After comparing all of the models, GRLA-ConvBiLST proved to be the most effective in every category.

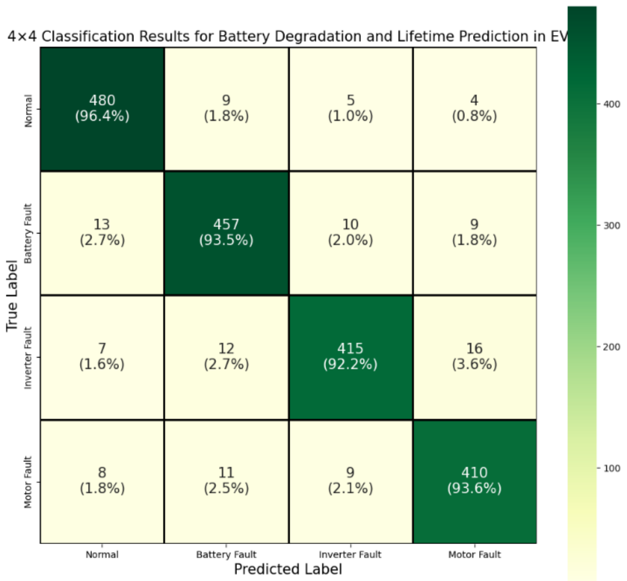

Fig 5. Confusion Matrix

For a visual representation of patterns of misclassification, see Fig. 5, which displays the confusion matrix. One particular table structure that helps to visualise algorithm performance is the confusion matrix. By contrasting the model's predictions with the actual target values, the matrix sheds light on the classifier's mistake categories.

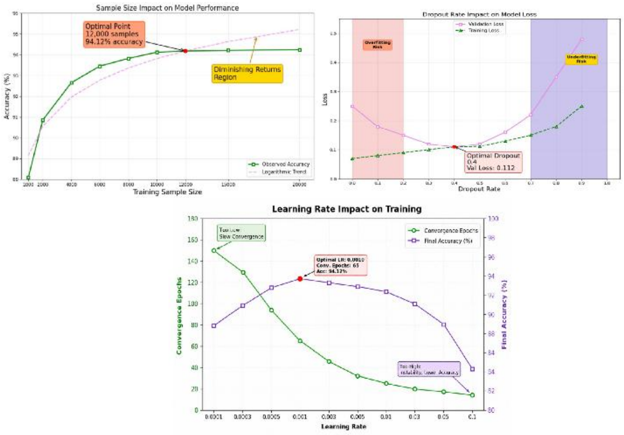

Fig 6. Hyper parameter and Data Impact on GRLA-ConvBiLST Model Performance

Fig. 6 shows the impact of three critical hyperparameters on the suggested model's ability to forecast battery deterioration. Finding the sweet spot that minimises validation loss while avoiding overfitting and underfitting is the goal of the dropout rate study, while the sample size analysis shows that prediction accuracy improves with larger training datasets until a stable optimum is achieved. Furthermore, the study of the learning rate reveals that the ideal learning rate is the optimum compromise between the convergence speed and prediction accuracy. This finding lends credence to the idea that optimising the model's hyperparameters properly improves both its performance and dependability.

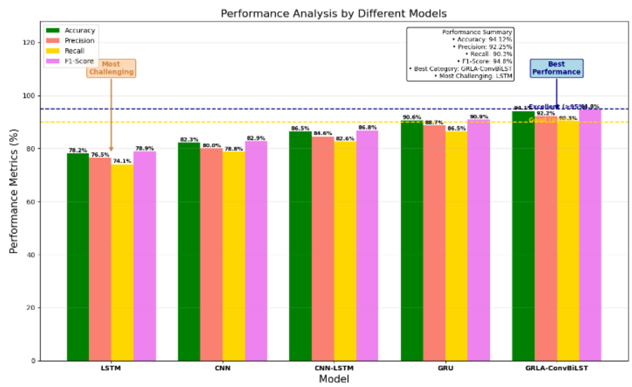

Fig 7. Performance Analysis for Models

The updated GRLA-ConvBiLST Prediction performance is compared to four other deep learning methods in Figure 7. Compared to the other four algorithms, the one based on the updated GRLA-ConvBiLST performs better.

CONCLUSION

For dependable integration into the car, stationary applications, and warranty concerns, it is crucial to be able to anticipate the lifetime of lithium-ion batteries under real operating conditions. Accelerated ageing tests are regarded as a potent alternative to the time and money spent on ageing testing conducted under real-world operating conditions. In order to forecast the RUL of lithium-ion batteries, this research suggests using preprocessed data from CEEMDAN. Data on battery capacity is decomposed into its high-frequency and low-frequency components using CEEMDAN. DV, DC, and ICA to extract electrochemical features thoroughly. To efficiently and accurately estimate the State of Charge (SoC) of lithium-ion batteries, they presented a novel hybrid ConvBiLST architecture in this study. Using the GRLA to fine-tune the ConvBiLST network's hyperparameters is a significant innovation in this work. A new method that reduces computational demands on deep learning models is the combination of GRLA with the ConvBiLST model. The model was shown to have greater accuracy and reliability in performance evaluations using a range of metrics, including Accuracy, Precision, Recall, F1-Score, and AUC. Outperforming state-of-the-art models from the present day, the model attained astonishingly high metrics: 94.12% accuracy, 92.25% precision, 90.30% recall, and 94.80% F1-Score.

Acknowledgement

The author would like to appreciate the effort of the editors and reviewers.

Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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