International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

Remaining Useful Life (RUL) Analysis of Deep Learning Approaches for Lithium-ion Battery

Manav Sapovadiya
Department of Computer Science and Engineering,
M.Tech CSE (Data Science) Student, Institute of Technology,
Nirma University,
Ahmedabad, India - 382481

***Abstract* - The accurate prediction of the Remaining Useful Life (RUL) of lithium-ion batteries is essential for their efficient use in energy storage systems, electric vehicles, and portable devices. This study examines how deep learning models - such as Convolutional Neural Networks (CNNs), Feedforward Neural Networks (FNNs), and Recurrent Neural Networks (RNNs) - can help forecast battery lifespan using operational and degradation data.A detailed analysis was conducted to identify the main factors affecting battery health, including the number of charge-discharge cycles and gradual capacity loss. To improve accuracy, the models were trained and tested on extensive datasets, with refinements made using the R^2 score. This study explores various deep learning models to evaluate how well they can track and predict battery aging over time. The findings reveal that deep learning techniques, especially RNNs, are highly effective in forecasting battery lifespan with great accuracy, making them useful for real-time monitoring. By improving battery health predictions, this research contributes to the development of smarter battery management systems, helping to enhance reliability and extend battery life.**

Keywords: Lithium-Ion Batteries, Remaining Useful Life (RUL), Convolutional Neural Network (CNN), Recurrent Neural Network(RNN), Feedforward Neural Network (FNN)

I. INTRODUCTION

Autonomy is greatly increased by linked hybrid energy storage when environmental and energy-related issues get worse[1]. Owing to continuously advancing product technology, lithium batteries are used in a wide range of industries, including smartphones, smart grids, unmanned aerial vehicles (UAVs), new energy vehicles, and airplanes. Despite their many benefits, lithium-ion batteries' performance will eventually decline as their operating period and charge-discharge cycle times increase. Because lithium-ion batteries are used as energy storage and supply units, their deterioration frequently fails in the entire system and even causes numerous safety incidents. [2].

A significant part of battery monitoring is the battery state of health (SOH), and that is a qualitative measure of the battery's
ability to store energy and transmit power[4]. One important yet difficult problem with Li-ion battery applications is tracking capacity deterioration and forecasting the remaining useful life (RUL). In real-world applications, a Li-ion battery's capacity would gradually decline over time as it faced several cycles of charging and discharging until its end-of-life (EOL). Both the battery's power and capacity would decrease far more quickly after EOL, which might further impede operations or perhaps result in an emergency. To guarantee that the batteries are used under dependable circumstances, it is essential to build the appropriate battery health diagnosis system (BHDS)[6].

When a battery reaches 80% of its initial capacity, which is known as the battery's end of life (EOL), its RUL is typically the number of cycles [7]. Battery manufacturing would benefit from accurate RUL prediction using early cycle data. Prediction using early cycle data, for example, would speed up the battery manufacturing cycle, enable manufacturers to validate new manufacturing processes quickly, and grade new batteries according to their anticipated lifespans [9]. The battery's material and the internal chemical reaction that occurs during charging and discharging have an impact on the battery's degradation process. Battery aging exhibits a very dynamic trend and is a significant process of change. [15,16].

In real-world use, factors including operating temperature, charge/discharge rate, and environmental stability will impact the battery's aging process and, in turn, its lifespan [13]. The steadily declining battery capacity is frequently employed as an effective health indicator in the field of lithium-ion battery RUL prediction in order tomonitor the battery's aging process.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

When a lithium-ion battery's capacity drops by 20–30% of its rated value, it is generally considered to have failed [15].

II. Literature Survey

First, in [1] Wang et al. attempt to improve the prediction of RUL of lithium-ion batteries through deep learning, comparing physics-based, machine learning, and hybrid models. They propose a CNN-LSTM framework that is more precise and better than conventional methods in identifying degradation patterns. However, the study encounters challenges related to dataset limitations and environmental variability, recommending future incorporation of physics-informed AI models for enhanced generalisation and robustness.

In [2] Jiaju Wu et al., the research introduces an innovative ensemble learning technique for predicting the RUL of lithium-ion batteries, integrating Relevance Vector Machine, Random Forest, Elastic Net, Autoregressive Model and LSTM networks; it utilises a Genetic Algorithm for optimal weight determination, exhibiting enhanced robustness and reduced RMSE relative to standalone models, yet encounters difficulties in managing varied operational conditions and comprehensive lifecycle prediction, indicating the need for advancements in multi-condition modelling and dataset adaptability.

In [3], Xifeng Guo et al. aim to forecast the remaining usable life (RUL) of lithium-ion batteries utilising a hybrid CEEMDAN-CNN-BiLSTM model. The primary contribution is the amalgamation of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise for data decomposition, 1D CNN for deep feature extraction, and BiLSTM for time-series forecasting. The outcome indicates the model proposed does a better performance in prediction precision than CNN-BiLSTM and BiLSTM models.The outcome demonstrates CEEMDAN enhances predictive performance by correctly eliminating mode aliasing.It has high demands on processing requirements and long prerequisite requirements as drawbacks that can hold it back for use in real time.

The objective of [4] Daniel Le et al. is to use voltage characterization (Ah-V) and ampere-hour throughput (Ah) to determine the state of health (SOH) of lithium-ion batteries. Using Ah-V functions and modeling tools such nonlinear logistic growth curves and quadratic fits, the main contribution is the development of new SOH estimate techniques based on battery energy storage capacity. The research concluded that the methods proposed can be used to accurately calculate a battery's State of Health (SOH) and closely approximate the conventional capacity-based calculations. The Ah-V method, in specific, is good at monitoring how batteries age, and SOH predictions become more accurate. However, there are some drawbacks. These methods require collecting a lot of data, can be affected by temperature changes, and may not work well for all types of batteries.

The objective of [6] Kailong Liu is to create a data-driven method for accurate prediction of future capacities and Li-ion battery residual usable life (RUL By combining Gaussian Process Regression with LSTM networks, the method effectively handles uncertainty and tracks long-term degradation patterns. The results have a high level of accuracy, with a maximum error of only 0.6% and an RMSE of 0.0032. The results demonstrate how LSTM and GPR complement one another in estimating uncertainty and long-term dependence, respectively. The computational complexity of hybrid modeling and its dependency on the quality of training data, however, are disadvantages.

[8] J JIANTAO QU aims to develop a neural-network-based method for tracking the State of Health and forecasting the Remaining Useful Life of lithium-ion batteries. For increased predictive accuracy, the main contribution is the combination of particle swarm optimization, the Long Short-Term Memory network, and an attention mechanism. The results indicate the effectiveness of CEEMDAN in real-time incremental learning and denoising data, with the developed method being superior to traditional methods. However, hybrid modeling's computational complexity and dependency on good-quality historical data are its limitations.

The goal of [9] Qing Xu et al. is to build a hybrid deep learning model for the early estimation of lithium-ion battery residual usable life. The fundamental contribution is the integration of deep-learned latent features and handmade features with domain knowledge, together with a unique snapshot ensemble learning strategy to improve model generalization and a non-linear correlation-based feature selection method. Based on the data obtained, the proposed model is superior to state-of-the-art approaches in terms of both primary and secondary test data sets. The outcome indicates that generalization and prediction accuracy are enhanced using statistical features and deep learning combined. The issue is that real-time implementation proves difficult because the approach has high computational and feature engineering demands.

The objective of [11] Mahrukh Iftikhar et al. is to employ a deep learning-based approach to optimize the prediction of the remaining usable life of lithium-ion batteries. The main contribution of this work is the development of the "AccuCell Prodigy" model, which combines auto-encoders with LSTM layers to improve prediction accuracy and efficiency. The findings show that the model decreases prediction errors substantially, with an R-squared of 0.9849, MSE of 0.1305%, MAE of 2.484%, and RMSE of 3.613%. The data indicate that the proposed model surpasses existing techniques in prediction accuracy and generalization. The issue is that the model requires large computational resources, making real-time deployment problematic.

In [14], Nicholas Williard et al. aim to examine the dependability and safety issues associated with lithium-ion batteries in aviation, specifically regarding the battery failures of the Boeing 787 Dreamliner.The main contribution is a comprehensive review of the problem of lithium-ion battery qualification, failure analysis, and risk assessment, along with suggestions for better battery management and safety practices. The results identify that the fundamental reason for the failures was never discovered, which revealed major shortcomings in existing battery reliability evaluations. The results identify that existing qualifying and testing procedures for lithium-ion batteries in aerospace systems are insufficient. The issue is that even though the research describes a number of remedies, it does not provide a comprehensive mechanism for preventing such mistakes in the future.

First, in [16] Jianfang Jia et al., the purpose is to predict the state of health and remaining useful life of lithium-ion batteries via indirect health indicators and Gaussian Process Regression .

The main contribution is the introduction of grey relation analysis to detect relevant IHIs from voltage, current, and temperature curves without requiring actual capacity measurements, improving prediction accuracy. The results confirm that this approach is better than traditional capacity-based models in estimating a battery's State of Health and Remaining Useful Life . With the utilization of Indirect Health Indicators , it makes the assessment easier without involving complex and time-consuming capacity measurements. This study suggests an improved approach that combines Support Vector Regression with an improved training data processing method through load collectives. This approach allows for more accurate estimations of a battery's State of Health and Remaining Useful Life under various usage patterns and environmental conditions. However, its accuracy depends on the quality and variety of training data, which may limit its effectiveness across different battery types and operating conditions.

[18] aims to evaluate the state of health and remaining usable life of lithium-ion batteries using a data-driven methodology.This research presents a better method that integrates Support Vector Regression with a more advanced training data processing technique employing load collectives. This method assists in making more accurate predictions of a battery's State of Health and Remaining Useful Life based on different usage conditions and environmental influences. The results show that this method provides precise predictions throughout the battery's life, making it practical for real-world use in battery management systems. Additionally, using load collectives enhances prediction reliability compared to traditional SVR techniques. The range of training data determines the model's accuracy, which may need a large amount of processing power.

[19] The objective is to predict the remaining usable life (RUL) of lithium-ion batteries using a deep learning-based approach, according to Lei Ren et al.. The primary contribution is the creation of an integrated deep learning model (ADNN), which combines a deep neural network (DNN) for estimate RUL across multiple batteries with an autoencoder for multi-dimensional feature extraction. With a precision rate of 88.2% and an RMSE of 11.80%, the outcomes illustrate that the proposed ADNN model outperforms Bayesian regression, support vector machines (SVM), and linear regression. The outcomes indicate that the autoencoder enhances predictability by effectively extracting battery degradation features. Because of poor feature representation, the model performs poorly for the late-stage battery degradation but excellently for early-stage and mid-stage degradation.

The primary contribution of [20] L. Li et al. is the incorporation of charging differential voltage inflection points and discharging peak values as indirect health factors for better capacity estimation; results indicate that the inclusion of these factors decreases RMSE by 16% and improves battery life prediction accuracy. The results highlight the effectiveness of Elman neural networks for recording dynamic battery behavior, but the limitation is dependence on quality training data and possible susceptibility to environmental change. The aim of the research is to predict the Remaining Useful Life (RUL) of lithium-ion batteries by a differential voltage analysis-based method and Elman neural networks.

[22] H. Feng et al. employ a better Gaussian Process Regression model to forecast the State of Health and Remaining Useful Life of lithium-ion batteries. The results show that the proposed model can obtain a SOH prediction error less than 0.02 and an RUL prediction error less than 10 cycles. The key contribution is combining five key characteristics derived from cyclic charging currents with the creation of a better kernel function to enhance prediction accuracy. While one limitation of GPR is that it relies on good-quality measurement data and extrapolating derived properties to all batteries, our findings illustrate the power of GPR in detecting trends in battery degradation with quantification of uncertainty.

The objective of [24] Shaoming Qiu et al. is to enhance the prediction of Remaining Useful Life (RUL) of lithium-ion batteries by resolving the noise interference and nonlinear degradation. The primary contribution is the incorporation of a hybrid IHSSA-LSTM-TCN predictive and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise pre-processing; experiments show that the proposed approach outperforms previous models in accuracy, showing the effectiveness of CEEMDAN in reducing prediction errors and improving robustness, and the drawback is the additional computational complexity introduced by multi-step pre-processing and hybrid modeling.

III. Methodology

Various factors impact Remaining Useful Life of the Lithium ion battery.The following characteristics improve the prediction for RUL like Cycle Index , Discharge Time, Max. Voltage Discharge, Min. Voltage Discharge, Time constant current, Charging time, etc.

A. Dataset Description

Lithium Ion battery Remaining useful cycle (RUL) found according to this Battery-RUL.csv which contains multiple censors and also battery degradation parameters. The main target variable for regression is the Remaining Useful Cycle(RUL).

	Cycle_Index	Discharge Time (s)	Decrement 3.6-3.4V (s)	Max. Voltage Dischar. (V)	Min. Voltage Charg. (V)	Time at 4.15V (s)	Time constant current (s)	Charging time (s)	RUL
0	1.0	2595.30	1151.488500	3.670	3.211	5460.001	6755.01	10777.82	1112
1	2.0	7408.64	1172.512500	4.246	3.220	5508.992	6762.02	10500.35	1111
2	3.0	7393.76	1112.992000	4.249	3.224	5508.993	6762.02	10420.38	1110
3	4.0	7385.50	1080.320667	4.250	3.225	5502.016	6762.02	10322.81	1109
4	6.0	65022.75	29813.487000	4.290	3.398	5480.992	53213.54	56699.65	1107

Fig. 1. Dataset

B. Dataset Preprocessing

Feature selection: In the feature Selection, cycle time, and voltage, there are many columns for feature selection but all of the other columns except RUL have independent variables.

Encoding: Binary Encoding using min, max scalar[0,1].

Data splitting: Data split into [80:20] training and testing data.

Also, This Methodology has three Models: CNN(Convolutional Neural Network), RNN(Recurrent neural network), and FNN(Feed Neural network) also compares CNN scores which have the best score, and finds the best score among these three models.

C. CNN model

In CNN model has 3 fully connected layers;

- Input layer: The number of neuron matches in the set was present in the input Layer.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

- Hidden Layer: In the hidden Layer each layer has RELU activation present first, second, and third respectively 128,64 and 32 neurons are presented.

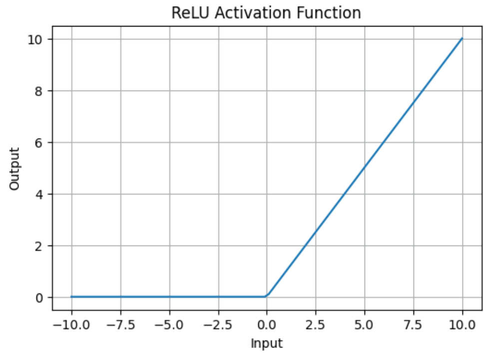

Fig. 2. ReLU Activation Function

- Output Layer: A single linear activation continuous RUL predictions.

This model trained in batch size of 32 and epoch of 100.

- Classification Of CNN model:

In classifications, numerical were always given input data have categorical value and output have always have categorical value.
In RUL prediction Binary classifications work according to this:

- Health(1):>1 is the threshold value of RUL.
- Near Failure(0): less than the threshold value of RUL.

- Performance Evaluation like:

In Performance Evaluation many metrics like Mean Square Error(MSE),Mean Absolute Error(MAE),Sum of Square Error(SSE),

R^2 Score is one of Evaluation:

$$R^2 = \frac{SSR}{SStot}$$

SSR (Sum of Squares for Regression) represents the variability explained by the regression model.
SStot (Total Sum of Squares) represents the total variability in the data.

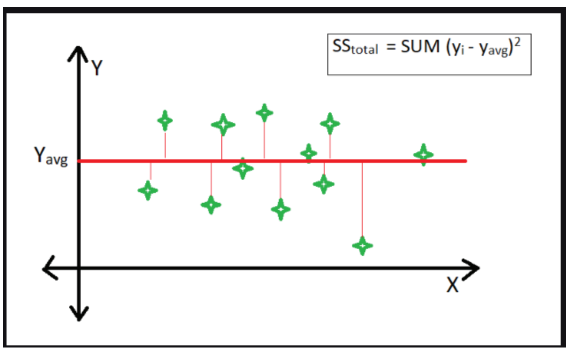

Fig. 3. SStotal

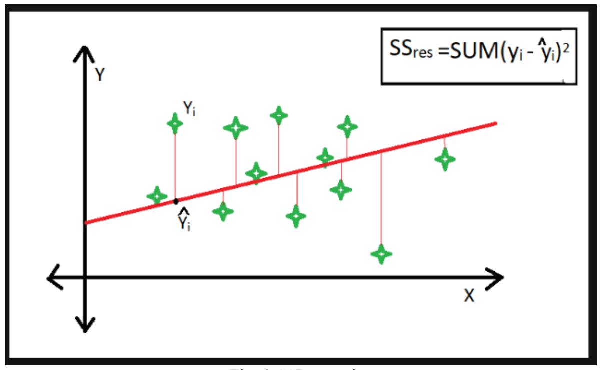

Fig. 4. SSRegression

D. RNN Model

- Model Arechitecure:

Long short-term memory (LSTM) is a specialised type of recurrent neural network (RNN) that excels in time series forecasting.
In contrast compared to conventional RNNs, LSTM incorporates a gating mechanism that facilitates information to be transmitted selectively [29]. The layout of LSTM is seen in Figure 2.

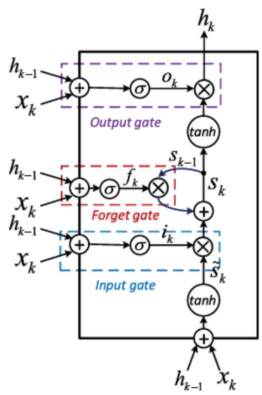

Fig. 5. RNN (LSTM)

The LSTM framework is that the important data can be stored or improved by changing the introduced gates. Furthermore, the LSTM model has the ability to retain knowledge for an extended duration.

Period devoid of gradient attenuation.
The atypical LSTM-based RNN model can be classified into three gate components, as depicted in Fig. 5. The states of all these gates can be gotten by the $X_{(k)}$ (the input at the current instant k) and $h_{(k-1)}$ (the output at the preceding instant k−1) by a sigmoidal unit. Input gate memory is added to the cell, while Forger gate Removes information in memory cell, and output gate controls information. These are three major works of three gates in memory cell: adding, removing, and controlling information.

1) Number of Layers (input, hidden, output).

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

2) ReLU and Sigmoid Functions are two (Activation Function).
3) Reduce Overfitting some Dropout Layer.

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2$$

J(V): This reflects the objective function or cost function. It is used to measure the overall within-cluster variance.
c: The number of clusters.
ci: The number of data points of the i-th cluster.

- Training :
  1) Loss Functions: For Regression R^2 score and classifications is used like Binary Cross Entropy).
  2) Hyperparameters like Batch size is 32 and epochs is 100 and also validation spilit is 0.2.

- Performance: Regression Metrics:

Two techniques, i.e R^2 Score (for train and test test) and MAE(Mean Absolute Error) , is used in evaluating performance.

$$MAE = \frac{1}{K}\sum_{k=1}^{k}|y_k - \widehat{y_k}|$$

$$R^2 = 1 - \frac{\sum_{K=1}^{n}(y_k-\widehat{y_k})^2}{\sum_{K=1}^{n}(y_k-\widehat{\bar{y}_k})^2}$$

E. FNN Model

- Model Architecture:

In FNN model has 3 fully connected layers

- Input Layer: The layer receives the neurons as there input data.
- Hidden Layer: Every neuron in a hidden layer takes a weighted sum as inputs followed by an activation function that is not linear.
- Output Layer: The output of the output layer produces the last result from the network.

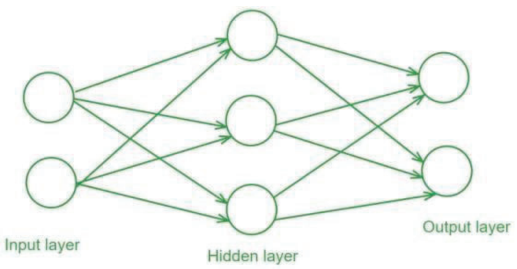

Fig. 6. FNN Architecture (Single Hidden Layer)

- Training a Feedforward Neural Network:

Building a FNN involves altering the weighting of the neurons to decrease the error between the expected output and the actual output. This method usually takes place via backpropagation and gradient descent.

1) Forward Pass: During forward pass, the source data passes through the network, and the output is identified.
2) Loss Estimation: The loss is determined using a loss function such as MSE for regression tasks or Cross Entropy Loss for classification jobs.
3) Backpropagation: In backpropagation, the error is carried through the entire network to modify the weights. The gradient of the loss function concerning each weight is determined, and the weights are changed using gradient descent.

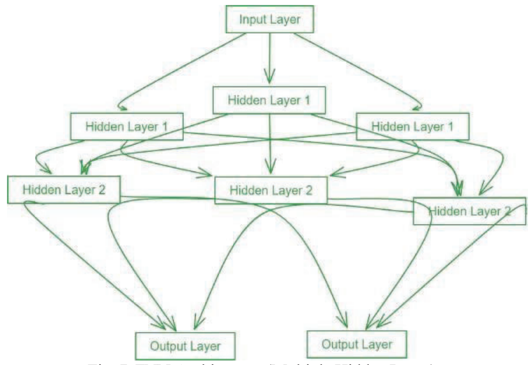

Fig. 7. FNN Architecture (Multiple Hidden Layer)

IV. RESULT

The work of analyzing the dataset obtained from 14 NMC-LCO 18650 batteries, cycled 1000 times at 25°C, is focused on predicting Remaining Useful Life (RUL) based on features extracted from voltage and current. The accuracy of three deep learning architectures—CNN, RNN, and FNN was compared with accuracy, F1-score, recall, and precision measures, along with R^2-scores for training and test sets.

A. Feature Importance Analysis

A feature importance analysis was conducted to explain the influence of multiple parameters on RUL prediction. This part explores each variable's importance in impacting battery degradation trends and model performance.

a. Most Influential Features:

Among all the variables retrieved, Discharge Time (F1), Time at 4.15V (F2), and Minimum Voltage Charge (F6) were the most dominant factors for predicting RUL.

- Discharge Time (F1) plays a crucial role in RUL estimate, as the longer the discharge time, the better the battery is usually. Its life diminishes over time as the batteries age, and it serves as a critical indicator of capacity degradation.
- 4.15V (F2) is another parameter that is very important. Lower endurance at this voltage level means that the battery does not store charge, an indication of premature degradation. This characteristic is useful in detecting minimal degradation of performance before loss of capacity becomes significant.
- Minimum Voltage Charge (F6) significantly affects RUL estimates since a consistent drop in the

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

minimum charge voltage reflects the loss of charge retention capability. This parameter is strongly associated with battery aging and is among the best cycle life predictors.

All these three factors together give a strong basis for predicting the duration for which a battery will keep delivering at its best.

b. Moderately Important Features:

Although less dominant than the top three, Time Constant Current (F3), Voltage Decrement from 3.6V to 3.4V (F4), and Total Cycle Time play a role as well in RUL prediction.

- Time Constant Current (F3) refers to the time a battery remains in its constant current charging stage. With age, this stage decreases, implying reduced efficiency in energy storage. While relatively significant, this characteristic enhances model performance when combined with other key variables.
- Voltage Decrement (F4) specifies the duration it takes for the voltage to decrease from 3.6V to 3.4V. Batteries with a quicker voltage drop within this range tend to show signs of degradation, so this feature is useful in identifying sudden changes in battery health.
- Total Cycle Time is the sum of charge-discharge time. Although it does to a certain extent reflect upon the overall process of aging, it is less accurate than more specific measures such as discharge time or voltage performance.

These characteristics add value by enhancing the accuracy of predictions, especially when combined with the most significant ones.

c. Least Influential Features

Certain features, like Maximum Voltage Discharge (F5) and Charging Time (F7), were limited in influencing RUL prediction.

- Maximum Voltage Discharge (F5) was relatively consistent for all cycles, which means it does not strongly correlate with trends in battery degradation. Since it does not present a clear trend over the lifespan of the battery, its contribution to prediction models is low.
- Charging Time (F7) also did not have sufficient predictability. While charging time does decrease with time, variations based on varying charging processes (e.g., quick charging and regular charging) impair its reliability as an RUL predictor.

These weaker characteristics indicate that even though they add more context, they are not major contributors toward deciding battery lifespan.

Feature	Description	Importance Score
F1	**Discharge Time (s)** – Duration of the battery discharge process.	High
F2	**Time at 4.15V (s)** – Time spent at 4.15V during the charge cycle.	High
F3	**Time Constant Current (s)** – Time spent in the constant current phase of charging.	Medium
F4	**Decrement 3.6V–3.4V (s)** – Time taken for voltage to drop from 3.6V to 3.4V.	Medium
F5	**Max. Voltage Discharge (V)** – Peak voltage value during discharge.	Low
F6	**Min. Voltage Charge (V)** – Minimum voltage reached during charge.	High
F7	**Charging Time (s)** – Total duration of the charging process.	Low
Total Time (s)	**Overall cycle duration (Charge + Discharge Time)**	Medium

Fig. 8. Importance score of the Dataset Features

d. Key Insights from Feature Analysis

The most essential measures of battery lifespan are Discharge Time (F1), Time at 4.15V (F2), and Minimum Voltage Charge (F6). These features should be prioritized in predictive models for RUL estimation.

Time Constant Current (F3) and Voltage Decrement (F4) contribute appropriately to forecasts and boost accuracy when used in conjunction with more prominent features.

Maximum Voltage Discharge (F5) and Charging Time (F7) had low impact on predicting battery health, showing that voltage peaks and overall charging length are less relevant in long-term RUL forecasting.

The results highlight the superior performance of the FNN model in regression and classification tasks, placing it as the most appropriate technique for RUL estimation in NMC-LCO 18650 batteries. The CNN model also performed exceptionally well, especially with regard to precision, making it a suitable alternative. The RNN model, although effective, demonstrated significantly lower accuracy and R^2-scores, indicating possible challenge in identifying long-term relationships in battery degradation processes.

The findings reflect that sophisticated deep learning architectures, more so FNN, efficiently forecast battery deterioration and Remaining Useful Life, critical towards improving energy storage systems as well as scheduling maintenance.

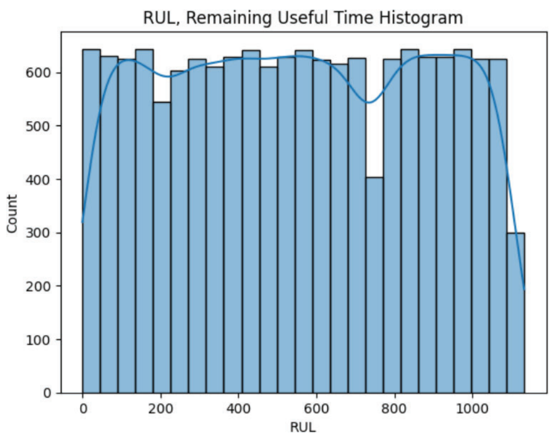

Fig. 9. Histogram of RUL

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

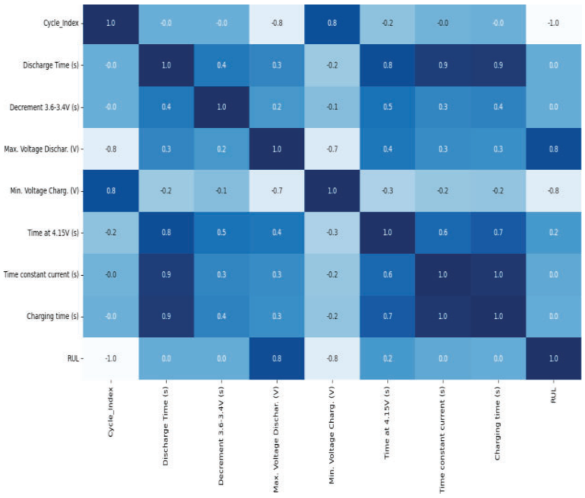

Fig. 10. Heatmap

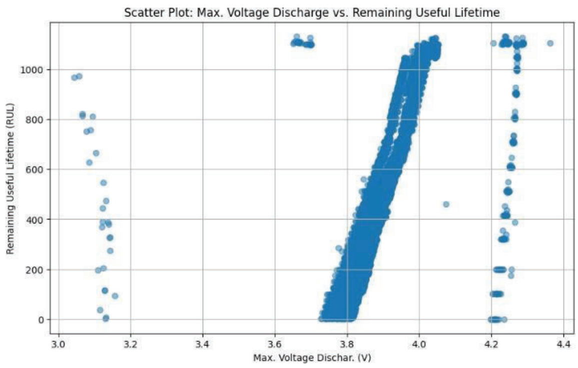

Fig. 11. Scatter Plot(Max. Voltage Discharge VS. RUL)

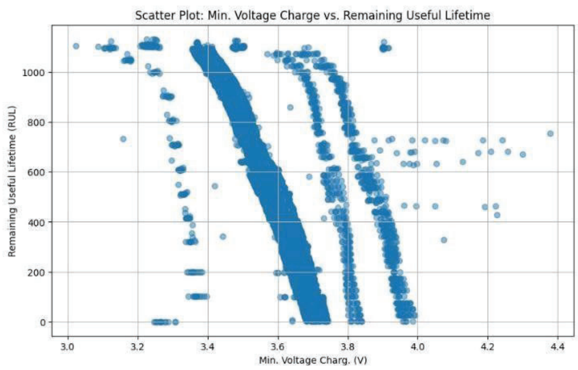

Fig. 12. Scatter Plot(Min. Voltage Discharge VS. RUL)

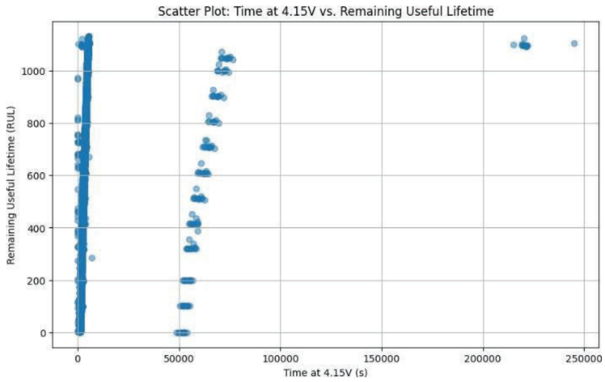

Fig. 13. Scatter Plot(Time VS. RUL)

e. Model Performance Metrics

Table 1 indicates the classification performance of the models regarding accuracy, F1-score, recall, and precision. The FNN model surpassed the other designs, attaining the maximum accuracy of 99.50%, an F1-score of 99.49%, a recall of 99.46%, and a precision of 99.53%. The CNN model attained an accuracy of 98.29%, whilst the RNN model acquired an accuracy of 98.31%.

Algorithms	Accuracy	F1-Score	Recall	Precision
CNN	98.29	98.28	97.91	98.66
RNN	98.31	98.31	98.11	98.51
FNN	99.50	99.49	99.46	99.53

Table. 1. Accuracy, Precision, Recall and F1-Score

f. Regression Analysis for RUL Prediction

To investigate the models' ability to predict the Remaining Useful Life (RUL) of the batteries, we analyzed their R^2-scores on both the training and test sets, as shown in Table 2. The FNN model displayed remarkable performance, earning a R^2-score of 99.95% on the training set and 99.55% on the test set, signaling great prediction accuracy. In contrast, CNN scored 96.26% on the training set and 96.28% on the test set, while RNN demonstrated the weakest performance, with a R^2-score of 87.60% on training and 87.71% on testing.

Algorithms	R^2-score on Training Set	R^2-score on Test Set
CNN	96.26	96.28
RNN	87.60	87.71
FNN	99.95	99.55

Table. 2. R^2-score on Training Set and Test Set

V. Conclusion

This study tested the effectiveness of three deep learning models in predicting the Remaining Useful Life (RUL) of NMC-LCO 18650 batteries using critical voltage and current features. The outcome revealed that Feedforward Neural

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

Networks (FNN) significantly outshined CNN and RNN models, achieving the highest accuracy, F1-score, and R^2-score. The most important predictors of battery deterioration were Discharge Time (F1), Time at 4.15V (F2), and Minimum Voltage Charge (F6), highlighting their relative importance in determining battery health and life over many cycles.

The outcome shows that deep learning RUL predictive models can be blended with Battery Management Systems (BMS) in order to advance real-time condition monitoring and upkeep approaches. Exact RUL forecasts allow organizations to maximize battery capacity, reduce service downtime, and ensure the security and dependability of energy storing systems. FNN performed most excellently when it came to generalization relative to the tested models, although RNN also experienced issues reading long-term development patterns, as a result, making it worse for this function.

Even though these models have good forecasting capability, other external parameters such as temperature fluctuations, disparate discharge rates, and operational conditions may affect battery life in practical applications. Future studies must include more environmental parameters in the models to enhance their generalizability to other types of batteries and application environments. Additionally, transfer learning and hybrid modeling approaches should be studied to strengthen the robustness of RUL predictions.

This research establishes a basis for more effective and sustainable battery management through the utilization of advanced deep learning algorithms. The incorporation of these predictive models into industrial applications can enhance battery longevity, reduce maintenance expenses, and aid in the advancement of more intelligent energy storage systems. Ongoing developments in model optimization and real-time deployment will persist in influencing the future of battery health monitoring and predictive maintenance.

VI. FUTURE REDIRECTION

In CNN model 4 Layers is Used, In Incresaseing layers -R^2 Score is drastically falling 0.9637 to 46 showing potential overfitting or vanishing gradient concerns.The objective is improve layer depth to balance generalization and accuracy. LSTM in RNN displays improved R^2 Improvement, showing consecutive correlations increase predictive performance.

Examine to FNN, both CNN and RNN show lower R^2 scores, necessitating adjustments to increase performance. Reducing Mean Absolute Error(MAE) and Mean Squared Error(MSE) is key to achieving parity with FNN. Optimization approaches including regularization, dropout, and hyperparameter tuning can boost model performance.

REFERENCES

[1]. Wang, S., Jin, S., Bai, D., Fan, Y., Shi, H., & Fernandez, C. (2021). A critical review of improved deep learning methods for the remaining useful life prediction of lithium-ion batteries. Energy Reports, 7, 5562-5574.

[2]. Wu, J., Kong, L., Cheng, Z., Yang, Y. and Zuo, H., 2022. RUL prediction for lithium batteries using a novel ensemble learning method. Energy Reports, 8, pp.313-326.

[3]. Guo, X., Wang, K., Yao, S., Fu, G. and Ning, Y., 2023. RUL prediction of lithium ion battery based on CEEMDAN-CNN BiLSTM model. *Energy Reports*, *9*, pp.1299-1306.

[4]. Le, D. and Tang, X., 2011, September. Lithium-ion battery state of health estimation using Ah-V characterization. In *Annual Conference of the PHM Society* (Vol. 3, No. 1).

[5]. Hasib, S.A., Islam, S., Chakrabortty, R.K., Ryan, M.J., Saha, D.K., Ahamed, M.H., Moyeen, S.I., Das, S.K., Ali, M.F., Islam, M.R. and Tasneem, Z., 2021. A comprehensive review of available battery datasets, RUL prediction approaches, and advanced battery management. *Ieee Access*, *9*, pp.86166-86193.

[6]. Liu, K., Shang, Y., Ouyang, Q. and Widanage, W.D., 2020. A data-driven approach with uncertainty quantification for predicting future capacities and remaining useful life of lithium-ion battery. *IEEE Transactions on Industrial Electronics*, *68*(4), pp.3170-3180.

[7]. Qu, J., Liu, F., Ma, Y. and Fan, J., 2019. A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion battery. *IEEE access*, *7*, pp.87178-87191.

[8]. Qu, Jiantao, Feng Liu, Yuxiang Ma, and Jiaming Fan. "A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion battery." *IEEE access* 7 (2019): 87178-87191.

[9]. Xu, Q., Wu, M., Khoo, E., Chen, Z. and Li, X., 2023. A hybrid ensemble deep learning approach for early prediction of battery remaining useful life. *IEEE/CAA Journal of Automatica Sinica*, *10*(1), pp.177-187.

[10]. Wu, L., Fu, X. and Guan, Y., 2016. Review of the remaining useful life prognostics of vehicle lithium-ion batteries using data-driven methodologies. *Applied Sciences*, *6*(6), p.166.

[11]. Iftikhar, M., Shoaib, M., Altaf, A., Iqbal, F., Villar, S.G., Dzul López, L.A. and Ashraf, I., 2024. A deep learning approach to optimize remaining useful life prediction for Li-ion batteries. Scientific Reports, 14(1), p.25838.

[12]. Zhang, Y., Xiong, R., He, H. and Pecht, M.G., 2018. Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries. IEEE Transactions on Vehicular Technology, 67(7), pp.5695-5705.

[13]. Jin, S., Sui, X., Huang, X., Wang, S., Teodorescu, R. and Stroe, D.I., 2021. Overview of machine learning methods for lithium-ion battery remaining useful lifetime prediction. Electronics, 10(24), p.3126.

[14]. Williard, N., He, W., Hendricks, C. and Pecht, M., 2013. Lessons learned from the 787 dreamliner issue on lithium-ion battery reliability. Energies, 6(9), pp.4682-4695.

[15]. Pang, X., Huang, R., Wen, J., Shi, Y., Jia, J. and Zeng, J., 2019. A lithium-ion battery RUL prediction method considering the capacity regeneration phenomenon. Energies, 12(12), p.2247.

[16]. Jia, J., Liang, J., Shi, Y., Wen, J., Pang, X. and Zeng, J., 2020. SOH and RUL prediction of lithium-ion batteries based on Gaussian process regression with indirect health indicators. Energies, 13(2), p.375.

[17]. Mao, L., Xu, J., Chen, J., Zhao, J., Wu, Y. and Yao, F., 2020. A LSTM-STW and GS-LM fusion method for lithium-ion battery RUL prediction based on EEMD. Energies, 13(9), p.2380.

[18]. Nuhic, A., Terzimehic, T., Soczka-Guth, T., Buchholz, M. and Dietmayer, K., 2013. Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods. Journal of power sources, 239, pp.680-688.

[19]. Ren, L., Zhao, L., Hong, S., Zhao, S., Wang, H. and Zhang, L., 2018. Remaining useful life prediction for lithium-ion battery: A deep learning approach. Ieee Access, 6, pp.50587-50598.

[20]. LI, L., LI, S., LI, J., SUN, K., WANG, Z., YANG, H., GAO, B. and YANG, S., 2021. RUL prediction of lithium-ion battery based on differential voltage and Elman neural network. Energy storage science and technology, 10(6), p.2373.

[21]. Liu, D., Luo, Y., Liu, J., Peng, Y., Guo, L. and Pecht, M., 2014. Lithium-ion battery remaining useful life estimation based on fusion nonlinear degradation AR model and RPF algorithm. Neural Computing and Applications, 25, pp.557-572.

[22]. Feng, H. and Shi, G., 2021. SOH and RUL prediction of Li-ion batteries based on improved Gaussian process regression. Journal of Power Electronics, 21, pp.1845-1854.

[23]. Zhao, J., Zhu, Y., Zhang, B., Liu, M., Wang, J., Liu, C. and Zhang, Y., 2022. Method of Predicting SOH and RUL of Lithium-Ion Battery Based on the Combination of LSTM and GPR. Sustainability, 14(19), p.11865.

[24]. Qiu, S., Zhang, B., Lv, Y., Zhang, J. and Zhang, C., 2024. A Lithium-Ion Battery Remaining Useful Life Prediction Model Based on CEEMDAN Data Preprocessing and HSSA-LSTM-TCN. World Electric Vehicle Journal, 15(5), p.177.