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ACCURATE BATTERY REMAINING USEFUL LIFE ESTIMATION USING AN ADVANCED MACHINE LEARNING APPROACH

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Abstract

The Remaining Useful Life (RUL) of lithium-ion batteries (LIBs), the foundation of modern energy storage systems and electric cars, must be precisely determined in order to provide safe, dependable, and predictive maintenance. Nonetheless, battery degradation is extremely nonlinear and depends on electrical, operational, and environmental factors that are very complex, which establishes the necessity to develop strong data-driven models that would be capable of representing the long-term trends in the aging process. This paper describes a developed machine learning (ML) model to accurately estimate the RUL with the multilayer perceptron (MLP) that was trained on the NASA Battery Dataset. The combination of a large amount of preprocessing, outlier treatment using IQR, feature scaling, and recursive feature elimination (RFE) is used to extract the most informative predictors. MLP optimized model has a high generalization, with a high R2 = 95.60%, RMSE = 1.14%, MSE = 1.302%, and MAE =7.982%. The comparison with the CatBoost, CNN-LSTM, and RNN models proves the high efficiency of the suggested model in degradation dynamics. The results show that using high-quality battery data sets and improved machine-learning architectures to forecast RUL may significantly increase the prediction's accuracy, which is a useful method for real-time battery management in EV and large-scale energy systems.

Keywords: Machine Learning, Lithium-Ion Batteries, Deep Learning, Remaining Useful Life (RUL), Battery Degradation Prediction, Electric Vehicles.

I. INTRODUCTION

Today, the technology of lithium-ion battery (LIB) production is in the stage of active global development due to the active investment of world corporations in the field of battery technology and the growing interest of researchers in developing the battery technology. Moreover, the world governments have come up with several green energy policies and plans to curb the emission of greenhouse gases, which are escalating the growth of the battery and other industries [1][2]. Consequently, the battery business has a high chance of becoming even more successful in the near future. Nevertheless, a notable disadvantage of LIBs is that the performance is gradually decreasing with time and use, and many factors determine this fact, as the LIB systems are rather complex systems [3][4].

But then, this booming expansion also increases the level of concerns with this issue as well as with battery life and health, and proper performance evaluation becomes even more important. There has been an impressive influx in the EV market due mainly to the development of the LIB technology. The fact that they have developed significantly in the past, unlike earlier, indicates the fact that they have gained acceptance as a legitimate substitute for internal combustion engines, which is a significant step toward environmentally friendly transportation.

Methodologies to forecast EVs' RUL have been developed as a result of their reliance on long-lasting and efficient batteries [5][6]. More accurate RUL prediction is crucial for EV safety and dependability, as well as for encouraging the circular economy by reusing batteries [7]. An efficient forecast model for battery degradation is challenging due to the extremely fragile nature of LIB, in addition to working temperature, circuit, load, and other external factors.

Recently, there has been a lot of interest in the data-driven approach to LIB RUL prediction research. However, the majority of data-driven techniques concentrate on producing short-term predictions for a single battery using the battery's previous data; very few current techniques are able to do multi-battery prediction using data from multiple batteries [8]. New data-driven solutions to this issue are brought about by developments in ML and DL. Higher prognostic efficiency and excellent computation efficacy are both possible with ML technology. The study concentrated on the feasibility of effectively applying data-based ML techniques in the field of RUL forecasting for LIB.

A. Motivation and Contribution of the Paper

LIBs are a major component of modern energy storage systems that power consumer devices, electric vehicles, and renewable energy infrastructures. In order to ensure safety, reduce maintenance costs, and increase operation reliability, qualitative forecasting of the RUL is essential. As sensor technologies and machine-learning capacity increase, data-driven prognostics, particularly with deep learning, have become a potential solution to the task of modeling battery aging trajectories. This motivates the current research to construct an efficient and scalable RUL prediction model based on cutting-edge ML. The major contributions made are:

- Used NASA battery data, which included the voltage, current, temperature, and capacity measurements with several charge-discharge cycles, to justify valid RUL prediction.
- Elaborated a full pre-processing pipeline, such as data cleaning, dealing with missing values, normalization and feature selection for model preparation.
- Applied the Multilayer Perceptron (MLP) model that was specifically created to predict RUL, which made it possible to capture nonlinear degradation patterns.
- Conducted model assessment based on MAE, RMSE and R2, which was a rigorous analysis of the model and allowed it to be compared with the current methods.

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B. Justification and Novelty of the paper

The necessity of precise, scalable, and generalizable prediction models of RUL is justified in this work by the critical requirement to scale to large, dirty and highly nonlinear battery data sets. Most of the available studies are either based on restrictive laboratory conditions, smaller feature sets, or are based on deep-learning architecture that consumes large amounts of computational resources. On the contrary, this paper also presents a new combination of rigorous pre-processing, RFE-based feature selection, and an optimized two-layer MLP architecture that can have high predictive accuracy and with reduced complexity. Its novelty is that it has end-to-end workflow that is used on large NASA data and is able to outperform CatBoost, CNN-LSTM, and RNN models in terms of performance as well as in an interpretable and efficient manner. The proposed framework is plausible in real-time battery-management applications, and this is due to its balanced design.

C. Outline of the paper

The paper structure is as follows: Section II provides a brief summary of relevant research on RUL prediction for LIB. Section III outlines the research approach that provided, such as the characteristics of the datasets, pre-processing, feature engineering, and model design of MLPs. Section IV gives the discussion and results of the experiment. The paper's conclusion and potential future study directions are provided in Section V.

II. LITERATURE REVIEW

This section provides a review of major ML and DL methods applied to lithium-ion battery health and RUL estimation. It outlines techniques, data, and performance results of recent research.

Zhang et al. (2022) present RUL prediction using an HPR CNN model. The residual network effectively retrieves hidden feature information at various depths by combining charging data from voltage, current, and temperature curves across numerous cycles. This technology does online prediction in a variety of practical applications by utilizing a cloud computing system with sparse data, accounting for only 20% of the charging capacity. When compared to previous approaches and validated using a public data set, the suggested method has a low test error of 4.15%. This shows promise for use in the context of a random billing procedure [9].

Du et al. (2022) provide a single DL approach that is suitable for both RUL and SoC estimations. The suggested method employs massive short-term memory recurrent neural networks to provide cutting-edge accurate capacity prediction for LIBs under challenging operating conditions. The unified method achieves outstanding precision in both one-step-ahead prediction and multistep-ahead estimation, with RUL estimation error within 10 cycles and SoC estimation error within 0.13%. The approach is trained using experimental data from the battery testing instrument under simulated complex operating conditions [10]

Bamati, Chaoui and Gualous (2022) an NARX estimator model is proposed for LIBs, with a focus on random missing measurements. The model performs real-time health diagnoses utilizing aging characteristics and their exponential moving average, demonstrating efficiency across missing data rates of 1% to 30% with MAEs and RMSs of about 0.6% [11].

Zhang et al. (2021) RUL estimation is significantly improved by the suggested method, which has been validated using both cyclic and noncyclic deterioration systems. An aero-engine system tested with three RUL models under two operating conditions yielded state-of-the-art results, with estimation errors reduced by 21.77% and 32.67%. Furthermore, with a lithium-ion battery system exhibiting cyclic degradation, the estimation error was negligible [12].

Xue et al. (2020) provide a technique for forecasting RUL using the BCT and capacity estimation. RFR is then used to produce accurate capacity estimation by training the model using only one cell's degradation data. Finally, the BCT-based linear model is utilized to forecast the battery's RUL. The PDF is calculated using the Monte Carlo (MC) simulation, which also analyses the forecast uncertainty. The experiment findings show that the suggested technique can estimate capacity with fewer than 2% errors and predict batteries' RUL with a maximum error of 127 cycles and a maximum span of 95% confidence of 37 cycles across the whole cycle life [13].

Basak, Sengupta and Dubey (2019) explain the selection process for several hyperparameters and talk about the lengthy short-term neural networks. Create methods for online predictions that include extensive data pre-processing, feature extraction, and validation using online simulation sets with variable hard disk usable lifespan. Describe the challenges of generating useful training sets from excessively chaotic and unevenly distributed large data. When a gadget is about to fail, the system does very well at estimating the battery's RUL close to the critical zone and can estimate with an average precision of 0.8435 whether a disk fails during the next ten days using the suggested method [14].

Table I, shows that various models, such as NARX, sparse GPR, BiLSTM, transfer learning, and capsule networks have produced high accuracy in showing LAB health and RUL prediction. In the vast majority, however, such models are only tested in special conditions or on individual data, and are thus not applicable to a variety of temperatures or load conditions and aging behaviour. There is also no single comparative framework provided in the existing literature to determine the most effective ML/DL methods to be applied and scaled practically. This emphasizes the necessity of generalized, benchmark, and powerful models that may be deployed to real-time electric vehicle (EV) systems, enhanced interpretability, ability to adapt to other battery chemistries, and adaptability to changing operating conditions.

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TABLE I. COMPARATIVE SUMMARY OF EXISTING STUDIES ON BATTERY RUL PREDICTION

Author & Year	Method / Model Used	Dataset	Key Objective	Performance Metrics	Limitations
Zhang et al. 2022	HPR CNN	Public battery dataset	RUL prediction using multi-cycle voltage, current, and temperature data	Test error: 4.15%	Relies on only 20% charging capacity data; may need cloud computing for online prediction
Du et al. 2022	Unified Deep Learning with LSTM	Experimental battery testing data under complex operating conditions	Unified RUL and SoC estimation with one-step and multi-step predictions	RUL error: ≤10 cycles; SoC error: 0.13%	Requires high-quality experimental data; model complexity may affect real-time deployment
Bamati, Chaoui & Gualous 2022	NARX Estimator	LIBs with simulated missing measurements	Real-time health diagnostics with missing data	MAE & RMSE <0.6%	Performance tested mainly on synthetic missing data rates; scalability to larger datasets uncertain
Zhang et al. 2021	Three RUL Models for Aero-engine & LIB systems	Aero-engine and LIB datasets	RUL estimation for cyclic and non-cyclic degradation systems	Estimation error reduction: 21.77% & 32.67%; zero error for LIB cyclic degradation	Limited focus on LIB datasets; generalization to other battery types not explored
Xue et al. 2020	RFR + Box-Cox Transformation + Ridge Regression	Single-cell degradation data	RUL prediction with uncertainty quantification	Capacity error <2%; Max RUL error: 127 cycles; 95% confidence span: 37 cycles	Offline training-based; may be limited with insufficient or noisy data
Basak, Sengupta & Dubey 2019	LSTM for predicting RUL	LIB datasets	Online RUL prediction of battery	Precision: 0.8435 for 10-day prediction	Model requires extensive pre-processing and feature extraction; performance may vary for highly unorganized or imbalanced datasets

III. METHODOLOGY

Predicting battery RUL is crucial for dependable energy management and maintenance scheduling. The dataset used in this study is NASA Battery Dataset comprising of 185,721 records with 12 variables, such as cycle number, capacity, voltage, current, battery temperature, and SOH representing the entire battery cycling under the controlled conditions. Figure 1 presents the overall approach of the methodology and depicts the end-to-end process of the workflow, encompassing data collection and pre-processing, model training and evaluation. Pre-processing of the data involves the removal of missing data, duplicates, merging data of batteries, engineering features of RUL and operational parameters, outliers through

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interquartile range (IQR) approach, and feature scaling to even out the numerical variables. RFE is carried out to select the twelve most informative features. A neural network with two layers and a multiple-layer perceptron (MLP) is used and is trained with hyperparameter optimization, and the evaluation was using MAE, MSE, RMSE, and R2 to guarantee the prediction of RUL is accurate.

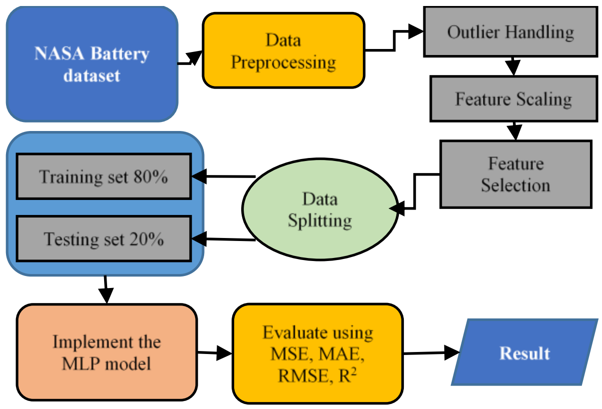

Fig. 1. Flowchart of the RUL Prediction of Batteries using Machine Learning

A. Data Collection

The dataset is a variation of the NASA Battery Dataset This was first released by NASA in 2010 and can be accessed on Kaggle. It consists of 185,721 records where 12 variables are in each entry and it records complete battery cycling in charge, discharge and impedance test profiles in a controlled ambient condition. Cycle number, ambient temperature, timestamp, capacity, voltage and current measured, battery temperature, load voltage and current, elapsed cycle time, SOH and battery ID are the variables. This useful run-to-failure time-series data is best used for prognostic procedures such determining RUL. The data collection process makes sure that all of the battery data and all of the metadata information are appropriately loaded into the analysis environment.

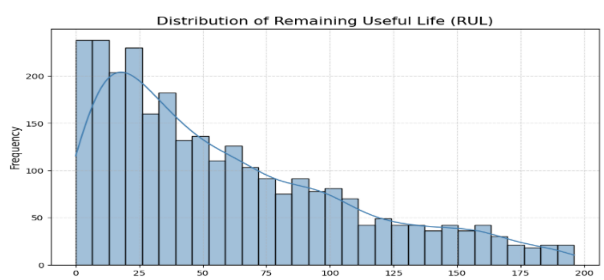

Fig. 2. Distribution of Remaining Useful Life (RUL) within the data

Figure 2 shows a histogram and a smooth density curve overlaid on the histogram showing the Distribution of RUL. The y-axis displays the frequency, with values peaking at 240, while the x-axis shows the RUL as the number of cycles remaining, beginning at 0 and finishing at 200. The distribution is evidently skewed to the right which means that most of the data values are clustered at the lower part of the scale. Namely, the very high frequencies are those within 0 and 25 cycles. The more left cycles there are, the smaller the frequency of the occurrences and this shows that there are fewer events that have a long left useful life.

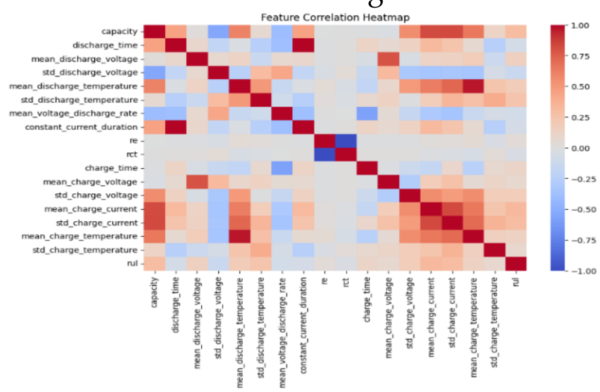

Fig. 3. Correlation Heatmap of the Dataset

The given Figure 3 shows the Feature Correlation Heatmap, representing the linear correlations among different parameters of battery operation and the target variable, RUL. The correlation coefficient, which ranges from a dark blue (strong negative correlation, -1.0) to a dark red (strong positive correlation, +1.0), represents the color's intensity. The diagonal axis represents a one-to-one correlation. More importantly, the lowermost row refers to the most important predictors' capacity, mean, charge, current and std charge current are some of the features that show significant positive correlation with rul (designated by the colours orange and red). On the other hand, the internal resistance measures such as re and rct exhibit weaker correlation. Also, the heat map shows groups of high multicollinearity between temperature and charging measures and this is the necessary information on the choice of features to maximize the predictive power.

B. Data Preprocessing

Data Pre-processing is the process of arranging, cleaning, and modifying raw data so that it may be analyzed or used in ML. Common steps include:

- Refine the raw battery data by removing gaps, fixing anomalies, ranking cycles and removing data duplication to provide correct time-series sequencing.
- Combine all single battery files into a single dataset and combine it with metadata to form an aggregate representation of battery degradation behavior.
- Extract operational parameters (voltage, temperature, current, capacity) and generate available indicators (average and rate-of-change) by generating the RUL label, and process them into more useful information; to improve the learning of the model.

C. Outlier Handling

Outliers are data points that lie far outside the bulk of the observations, which are usually due to either measurement errors or noise or infrequent events [15]. They are able to alter statistical processes and have an adverse effect on ML models by either biasing the prediction or adding variance. The interquartile Range (IQR) method is one such common method of dealing with outliers, which determines the values that are not within the IQR below the first quartile or above the third quartile and cuts off such values to those boundaries.

D. Feature Scaling

The numerical dataset is subjected to the usual scaler normalization procedure, which permits standardization of the features by changing the distribution mean [16]. This guarantees that the majority of the dataset's values fall between 0 and 1. It assures and prevents larger-scale features from dominating the learning process. The mathematical expression of standard scaler is represented as follows by Equation (1):

$$z = \frac{x-\mu}{\sigma} \qquad (1)$$

E. Feature Selection

RFE is used in feature selection to enhance model performance and reduce overfitting risk. Under this method, a base estimator, i.e., a Random Forest, ranks the importance of all features. The insignificant features are eliminated one by one until only a specified number of best features are left out. In this case, it is a dozen most predictive features. With these chosen characteristics, the model can be used to concentrate on the most informative signals in the battery data which enhances predictive performance as well as interpretability. The process of feature selection also makes the computational complexity lower and enables the model to be more generalized to unseen cycles.

F. Dataset Division

The dataset is divided, often in an 80:20 ratio, into train and test sets. As a result, the model may identify trends in the training set and be evaluated using unidentified test data.

G. Proposed MLP Model

The feedforward multilayer perceptron (MLP) is the most widely used NN design; in this work, a two-layer MLP is used instead. The device's state of degradation as a function of time is represented by the NN architecture. The input and output nodes represent the variables, respectively. To determine the associated deterioration state—capacity (battery), the input node accepts time in cycles (battery) as input [17]. Hidden neurons are nonlinear nodes that form the hidden layer, which connects the input and output nodes. Each layer conveys information using an activation function [18]. A sigmoid activation function divides the input and hidden layers, whereas a linear activation function separates the hidden and output layers. Equation (2) expresses the sigmoid activation function in terms of neural network parameters (bias and weights):

$$h_i = \frac{1}{1+e^{-(w_i^{(1)} \times k + b_i^{(1)})}} \quad (2)$$

where hi(.) is the tan-sigmoid activation function corresponding to the input layer, k is the time index, i = 1,..., M is the number of hidden neurons, and w_i^((1)) and b_i^((1)) Are the input weight and bias corresponding to the ith hidden neuron. The anticipated capacity/light output at the output node can be expressed using equation (3)

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$$g\left((w,b),k\right) = f\left(\sum_{i=1}^{M}\left(h\left(\left(k \times w_i^{(1)} + b_i^{(1)}\right)w_i^{(2)} + b_i^{(2)}\right)\right)\right) \quad (3)$$

The MLP network output is denoted by g((w,b),k), h(.) is the tan-sigmoid activation function between the input and hidden layer, and w_i^((2)) and b_i^((2))Re the weight and bias values at the hidden layer.

H. Model Training

The model is trained to forecast battery RUL through MLP NN. Randomized Search with cross-validation is used to modify a number of hyper parameters, including the type of solver, learning rate, regularization intensity, activation function, number of neurons per layer, and number of hidden layers. This process considers a variety of hyper parameter combinations chosen randomly, and cross-validation is applied to each of them to measure their performance. The best performing configuration is picked and the final MLP is then trained using the full Tested set and training using the test set to guarantee precise and generalizable predictions of RUL.

I. Evaluation Metrics

Additionally, the MAE, RMSE, MSE, and R square (R^2) are used to assess the algorithms' RUL prediction accuracy [19]. R^2 is the proportion of the variance of the dependent variable in a regression model that can be accounted for by any number of independent variables. For quantitative data, RMSE is a widely used method for estimating a model's prediction error. The average squared difference has also been computed using the MSE [20]. Additionally, MAE displays the typical discrepancy between actual and expected forecasts. Equations (4) through (7) define them.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^{\dot{P}})^2} \quad (4)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_1\right)^2 \quad (5)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_1\right| \quad (6)$$

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i-1}^{n}(y_i - \bar{y}_i)^2} \quad (7)$$

These assessment indicators all give a clear picture of the RUL estimate models' prediction accuracy and dependability, making it possible to assess the models' effectiveness.

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IV. RESULTS & DISCUSSION

The purpose of the study was to obtain precise estimation of battery RUL with sophisticated ML models, with the emphasis on a MLP. The experiment was conducted using a laptop with an NVIDIA graphics card, an Intel Core I7 CPU, and 16GB of RAM that processed data on LIB under standardized specifications using Python 3.11. The fundamental libraries were NumPy and Pandas to work with the data and Tensor Flow/Keras to apply the MLP. The model showed a very good predictability as indicated in Table II, with a 95.60% R-squared value, 1.14% RMSE, 1.302% MSE and 7.982% MAE error which showed that there is very little difference between actual and predicted battery life. The results demonstrate that the combination of reliable battery data and strong machine learning models can produce incredibly accurate RUL estimates, which is why this approach is ideal for BMS in electric cars and energy storage systems.

TABLE II. PERFORMANCE METRICS OF THE MLP MODEL FOR BATTERY RUL PREDICTION

Metrics	MLP
R-squared value	95.60
RMSE	1.14
MSE	1.302
MAE	7.982

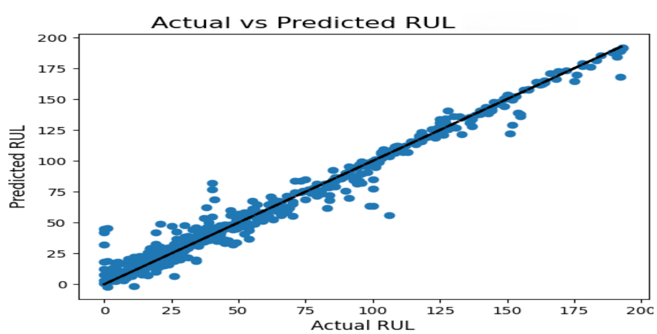

Fig. 4. Actual vs. Predicted value of MLP Model

Figure 4 displays a scatter plot of the performance of a MLP model in predicting Battery RUL. It uses a scale of 0 to 200 to plot ground truth RUL values on the x-axis and the model's predicted values on the y-axis. A black diagonal line is to be a solid one that is the identity line of y=x and where ideal predictions would be. The blue data points are tightly distributed around this line thus showing a strong positive linear correlation and hence they are highly predictive. Despite the small deviations that can be observed in the bottom RUL (050) spectrum (approximately small scatter), the general proximity of the two attests to the fact that the MLP model is effective in extrapolating the battery degradation data, which leads to a small error and to a high fidelity to prognostic predictions regarding the remaining battery life.

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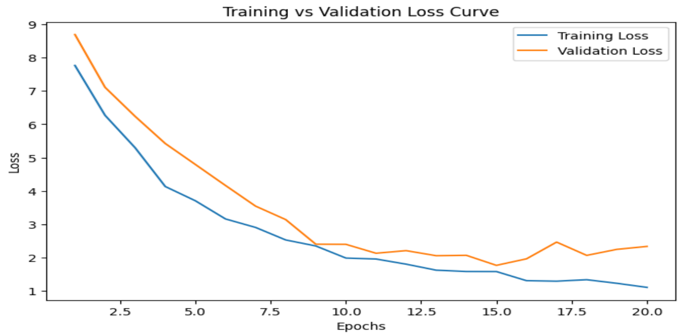

Fig. 5. Training and Validation Loss of the MLP model

The Training vs. Validation Loss Curve of the MLP model, which is intended to be used to forecast the Battery RUL over a span of 20 training epochs, is displayed in Figure 5. The graph uses the number of epochs as an independent variable and the loss magnitude as the dependent variable. The Loss in Training (blue line) shows a smooth and steady negative slope, that is, the loss value is reducing with starting at about 8.0 to almost 1.0, which shows that the model is actually learning the battery degradation patterns. Validation Loss (orange line) is closely associated with training loss during the initial 15 epochs which is a good indication of its ability to generalize. But during the last five epochs the validation loss has been stabilized and oscillates slightly about 2.0 as the training loss keeps decreasing. This minor deviation means that the model has converged and the best model performance is probably obtained at the epoch of 15 when there is slight over fitting.

A. Comparative Analysis

This section compares how well several sophisticated ML models perform in accurately estimating batteries' remaining usable life (RUL). Table III below explains the comparative performance of the selected models using the values of R-squared below.

TABLE III. COMPARATIVE PERFORMANCE OF MACHINE LEARNING MODELS FOR BATTERY RUL ESTIMATION

Models	R-squared value
CatBoost[21]	94.85
CNN-LSTM[22]	94.0
RNN[23]	91.7
MLP	95.60

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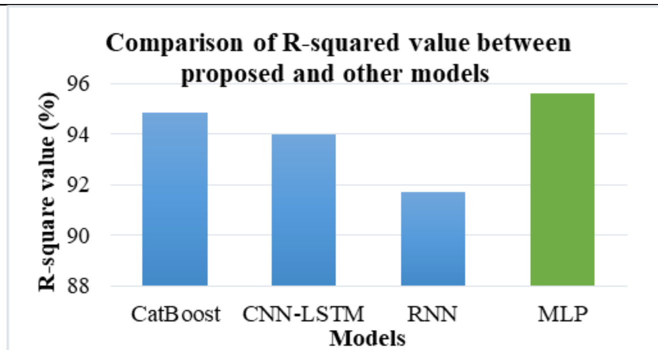

Fig. 6. Comparison of R-squared value between proposed and other models

The bar chart in Figure 6 and Table III gives a comparative performance comparison of the proposed Multi-Layer Perceptron (MLP) model with three other state-of-the-art algorithms to predict Battery RUL CatBoost, CNN-LSTM and RNN. The R-squared value is the measurement metric, which is the goodness of fit. The best performance with the highest R2 of more than 95.6% is obtained with the proposed MLP model with the green bar. This performs much better than the RNN (91.7%) and CNN-LSTM (94.0%) models, as well as the CatBoost model (94.85%). The graphic comparison in a bar chart clearly shows that the MLP architecture has a high ability to represent the underlying degradation pattern of the battery data and as such, its selection as the best model is accurate and reliable in estimating the RUL in this paper.

V. CONCLUSION & FUTURE WORK

The investigation expressions that the proposed ML framework is a useful and efficient method for predicting the RUL of LIB using the NASA Battery dataset. After structural preprocessing, carefully designed electrochemical characteristics, and an optimized MLP architecture, the model can capture nonlinear degradation patterns and has a good predictive ability with a high R2 value of 95.60%. This result shows that the model can closely estimate the real degradation behavior through a series of battery cycles, indicating its high strength and usefulness in battery prognostics, safety insurance and cost-efficient maintenance scheduling. The visual analyses also accompany this, and show uninterrupted prediction behavior and interpretability in the overall trend of degradation in the long run, which aid in making improved decisions in BMS. Despite the impressive performance of the suggested strategy, there are a number of opportunities that can be enhanced. The future research can expand the datasets available and investigate more diverse ones, such as those of real-world electric-vehicle or renewable-storage profiles, to maximize the generalization and robustness in a variety of operating circumstances. The integration of mechanisms of online learning might facilitate the continuous change in response to the changes in battery behavior over time. Moreover, the incorporation of the uncertain estimation and explainability would be more appropriate to enhance transparency and trust and make the framework more adaptable to the mission-critical setting. Further refining prediction stability and scalability can be done by increasing feature engineering strategies and testing other ML models. All these improvements will help to create stronger, interpretable, and industry-ready RUL prediction systems.

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