Interpretable Deep Learning Approach for Long Horizon Health Prognosis of a Li-ion Battery

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***Abstract*—The safety of a wide range of devices depends on the accurate long-term estimation of the State-of-health (SoH) of Lithium-ion battery. However, the existing techniques have several limitations in terms of prediction accuracy, computational complexity and applicability. To mitigate these drawbacks, a novel Deep learning-based method with low computational complexity has been proposed that can predict battery's future performance upto 100 cycles, thereby providing an early warning of battery failure. A unique feature called Interval of time for spectrum of same charging voltages (ITSSCV) along with maximum and minimum voltages for each cycle are used to predict the SoH of the battery, which greatly reduces the size of the training data and the storage requirements. A Long Short Term Memory (LSTM) neural network has been utilized to predict the SoH with 0.005 RMSE. Further, the proposed solution can perform the long horizon SoH estimation upto the next 100 cycles with an RMSE of 0.0029. Moreover, Explainable AI is applied to the model to interpret the prediction outcome and improve trustworthiness. The model can quickly and accurately predict the long horizon SoH of battery using low-end computation resources, thereby proving its usefulness in real-life critical battery-operated equipment.**

***Index Terms*—State-of-health, Lithium-ion Battery, Long horizon, ITSSVC, Long Short Term Memory.**

I. Introduction

Due to the high energy density, high efficiency, and decreasing manufacturing costs, Energy Storage Systems based on lithium-ion cell technologies, Lithium-ion batteries are quickly taking over a wide range of storage uses. Despite their robustness, the motors may malfunctioning due to harsh working conditions, high temperature, high humidity, and overloading, leading to unexpected downtime [1], [2]. Eventually, LIB's efficiency would decline because of ageing and operating environment factors. The unexpected failure may result in emergent maintenance and unexpected system shutdown, which can be catastrophic [3]. To guarantee a satisfactory performance, it is critical to precisely determine the state of health (SoH) of LIBs.

Numerous methods have been described in recent years for the SoH estimation of LIB.The following list is a general breakdown of these strategies: Open-Circuit Voltage (OCV) Method, Coulomb Counting Method, Impedance Spectroscopy Method, Model-Based Method, Artificial Intelligence (AI) Method. Though there are different methods for the estimation of SoH, there are limitations to each of the methods. In open circuit voltage method, the OCV is affected by a number of factors such as battery's previous charging and discharging history. These factors can cause the OCV to vary, which can make it difficult to accurately estimate the SoH of the battery. A disadvantage of the Coulomb counting method is that it does not account for the effects of temperature on the battery. Changes in temperature can affect the efficiency of the battery's charging and discharging processes, leading to inaccuracies in the estimated SoC. A disadvantage of impedance spectroscopy method is that it requires specialized equipment and expertise to perform the measurements and interpret the data. This can make it challenging and costly for non-experts to use the method. A disadvantage of model-based methods is that they can be computationally expensive and require a significant amount of processing power. This can limit their practicality in real-time applications, such as electric vehicles, where rapid and accurate SoH estimation is required. Though there are many algorithms in the field of machine learning for the prediction of SoH, most of the algorithms used are either complex models or cannot be deployed in real world. So our motivation is to build a :

- Low complex model and costeffective model, so that it can be deployed on board.
- Know the battery health status of the Li-ion battery

With this motivation, we have devised a model that can anticipate the SoH of the battery using a unique feature that has been extracted and have found some breakthrough results.The process flow of the prediction is shown in Fig 1. The major contributions of this paper are:

- The paper proposed a low-complexity and cost-effective solution using Deep Learning to accurately estimate the state-of-health (SoH) of lithium-ion batteries.

- The proposed technique involves the extraction of a unique feature called Interval of time for spectrum of same charging voltages (ITSSCV).
- Long horizon health prognosis of the battery for the next 100 cycles has been done using the Long Short Term Memory (LSTM) algorithm, which gives an RMSE of 0.005.
- Explainable AI is used to interpret the proposed black box DL model to improve its interpretability and trustworthiness.

This papers follows the order of Introduction followed by Related works where there would be a discussion on the other research papers, the proposed system for this current paper including the structure of the proposed model, battery health indicator extraction, Prediction of SoH, Explainable AI, Long horizon prediction followed by results and discussion on comparision with various models and concludes with conclusion and future scope.

II. Related works

Currrently a lot of reseachers are working on EV batteries and the their performance. Despite significant progress in this field, several limitations exist in the current battery health management systems. For instance, some systems rely on complex models that require significant computational resources, which may not be suitable for certain applications with limited processing power.To address these limitations, recent studies have proposed new approaches for intelligent battery health management. For instance, in [2] the proposed SoH estimatiom system does not explicitly mention the factors that contribute to battery health and its potential limitations include high dependence on model parameters, limited applicability to all types of Li-ion batteries or operating conditions, assumption of similarity between aged and fresh batteries, need for partial charging data, and room for improvement in accuracy. These considerations might impact the accuracy and generalisability of the SoH estimate technique suggested. The proposed ensemble learning-based data-driven method in [3] does not address the limitations of current battery health management systems in adapting to changing operating conditions.

To improve the proposed intelligent battery health management system, it could incorporate elements from these studies, such as the use of ensemble learning algorithms [3], [5] particle filter algorithms [6], and neural networks [7], to enhance the accuracy and reliability of battery health prediction. Additionally, the system could incorporate an adaptive control algorithm, as proposed by the current study, to adjust battery operation based on changing operating conditions and improve the overall performance and efficiency of the battery system. In [7], the method uses a combination of a neural network and a fuzzy logic system to estimate the battery's SoH based on its performance data. However, the method does not address the limitations of current systems in adapting to changing operating conditions or incorporate an adaptive control algorithm. The authors did not compare their multi-task learning approach to other SoH and RUL prediction methods.

Zhang et al. [8] proposed a new method that requires a large amount of training data, which may not be available in some applications. In [11], the complexity of electrochemical processes within the battery makes it impossible to exactly identify the aging mechanism and quantify the SoH. In [12], the model relies on complex preprocessing and several charge/discharge cycles for feature extraction, which may not always be viable. Methods like Incremental Capacity Analysis (ICA) and Differential Voltage Analysis (DVA) are susceptible to noise, restricting their applicability. In [13] lacks a comparative analysis with other approaches, does not explain the computational cost of the proposed methods, and lacks experimental validation on real-world battery cells. However, more research is needed to validate the method on a larger dataset and to develop techniques to mitigate the effects of noise and other factors that can reduce the accuracy of the SOH estimation. In [14], the method is sensitive to noise in the battery voltage signal. This may reduce the accuracy of the SOH estimation in real-world applications. The summary of all the related works along with the remarks are shown in Table I.

III. The Proposed System

The process flow for the detection of SoH of proposed system is depicted in Fig. 1.

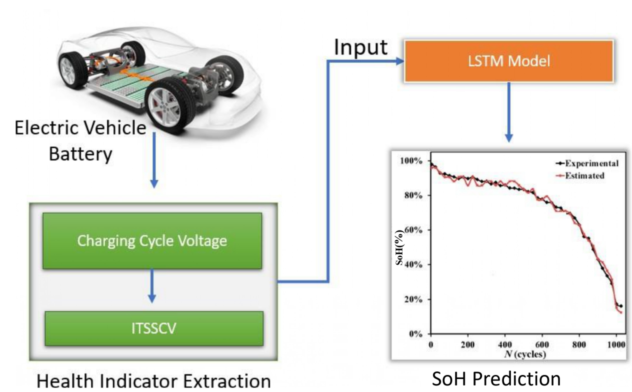

Fig. 1. The process flow for the estimation of SoH.

A. Structure of the proposed method

In this article, the Health indicator extracted from the dataset is interval of time for spectrum of same charging voltage (ITSSCV). The extracted features are then mapped to the SoH of the battery with their corresponding cycles using the LSTM model with one LSTM layer and one dense layer.

B. Battery Health Indication Extraction

The dataset used in this paper is taken from Toyota Battery Dataset. Although direct HIs are particularly successful in forecasting the battery's SoH and RUL, they are difficult

TABLE I
COMPARISON OF EXISTING SOLUTIONS

Author	Dataset	Model	Evaluation Metrics	Remarks
S. Zhang et al [4]	Lab data	Particle swarm optimization, Extreme Learning Machine	MAE: $\pm 4\%$	No physical interpretation of the results
G. Li et al [5]	Collected data from 5 vehicles	Extreme Learning Machine	MSE: 0.169 MAE: 0.308	Limited explanation of the ensemble method
Y. Song et al [6]	4 NCM li-ion battery cells cycling test data	Particle filter-based model	MAE: 0.85% (least MAE)	Highly computational and the scalability of model is limited
P. Jain et al [7]	Self obtained OCV dataset	Data-driven method, (includes SVM, ANN)	RMSE: 3.36% MAE: 2.25%	Lack of model interpretability
D. Chang et al [8]	RTM data provided . by one OEM	LSTM - (Long short -term memory)	MAE: 0.009	Lacks transparency and interpretability of the model.
M. Vatani et al [9]	Self measured ICA data	Support Vector Machine	MAE: 1.86%	Limited feature extraction
G.You et al [10]	Lab test data	SVM,ANFIS(Adaptive Neuro-Fuzzy Inference System	RMSE: 0.021	Lack of sensitivity analysis
Current Paper	Toyota dataset	LSTM - (Long short -term memory)	RMSE: 0.005 MAE: 0.0039	Low complex model with model interpretability and long horizon prediction of up to 100 cycles

to deploy for online applications.In practise, The parameters such as current and voltage are usually considered to be HIs that are commonly used in online battery life forecasting.In real life, indirect HIs such as current and voltage are widely employed in online battery life prediction. Therefore, a vital HI is the interval of time for spectrum of same charging voltage in the course of the battery's charging and discharging cycles. Yet, given that the discharging cycle changes with various load characteristics in extremely different online consumption, the time interval for spectrum of similar charging voltage during charging phase is considered as an improved HI for SoH evaluations.This time span reduces as the number of cycles raises and is regarded as interval of time for spectrum of same charging voltage (ITSSCV), as shown below in Fig. 2.

Here we will get three time intervals i.e., time in which the voltage went from 33^{rd} percentile to 66^{th} percentile, 66^{th} percentile to 99^{th} percentile and 33^{rd} percentile to 99^{th} percentile for each cycle. This is given by the equation:

$$ITSSCV(V_{\min}, V_{\max}) = t_{v_{\max}} - t_{v_{\min}}, \quad (1)$$

where V_{min} and V_{max} are the lowest and highest values of the chosen charging voltage range, respectively. The time gap between when the terminal voltage of the battery reaches V_{min} and V_{max} are represented by $t_{V_{max}}$ and $t_{V_{min}}$.

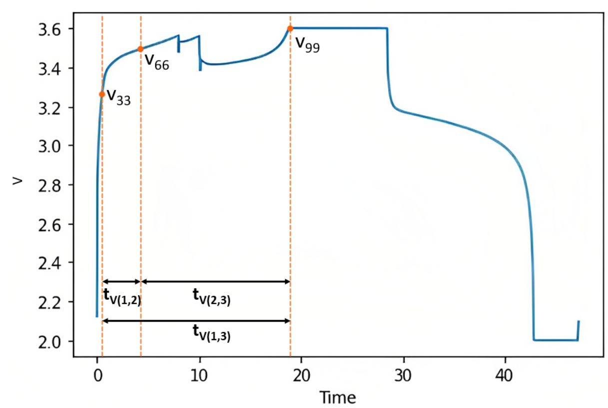

Fig. 2. Exctraction of ITSSCV.

C. Prediction of SoH

The battery pack is one of the most critical components of an EV, and it is responsible for storing the energy that powers the electric motor. Over time, the battery's ability to hold a charge and deliver power will deteriorate, and this is reflected in the battery's State of Health. It's important to note that several factors can affect the battery's State of Health, including temperature, usage patterns, and charging habits. Though many facors such as load, temperature and other factors effect the SoH of the battery, as the model is data driven, all such effects due to those factors will effect the data directly and thet model will reflect on these effects. Extreme temperatures, frequent deep discharges, and rapid charging can all accelerate the battery's degradation and reduce its State of Health. By monitoring the State of Health and taking appropriate measures to mitigate degradation, the overall performance and longevity of the battery can be maximized. The Health Indicators that are extracted from the dataset are extremely useful for the prediction of State of Health of a

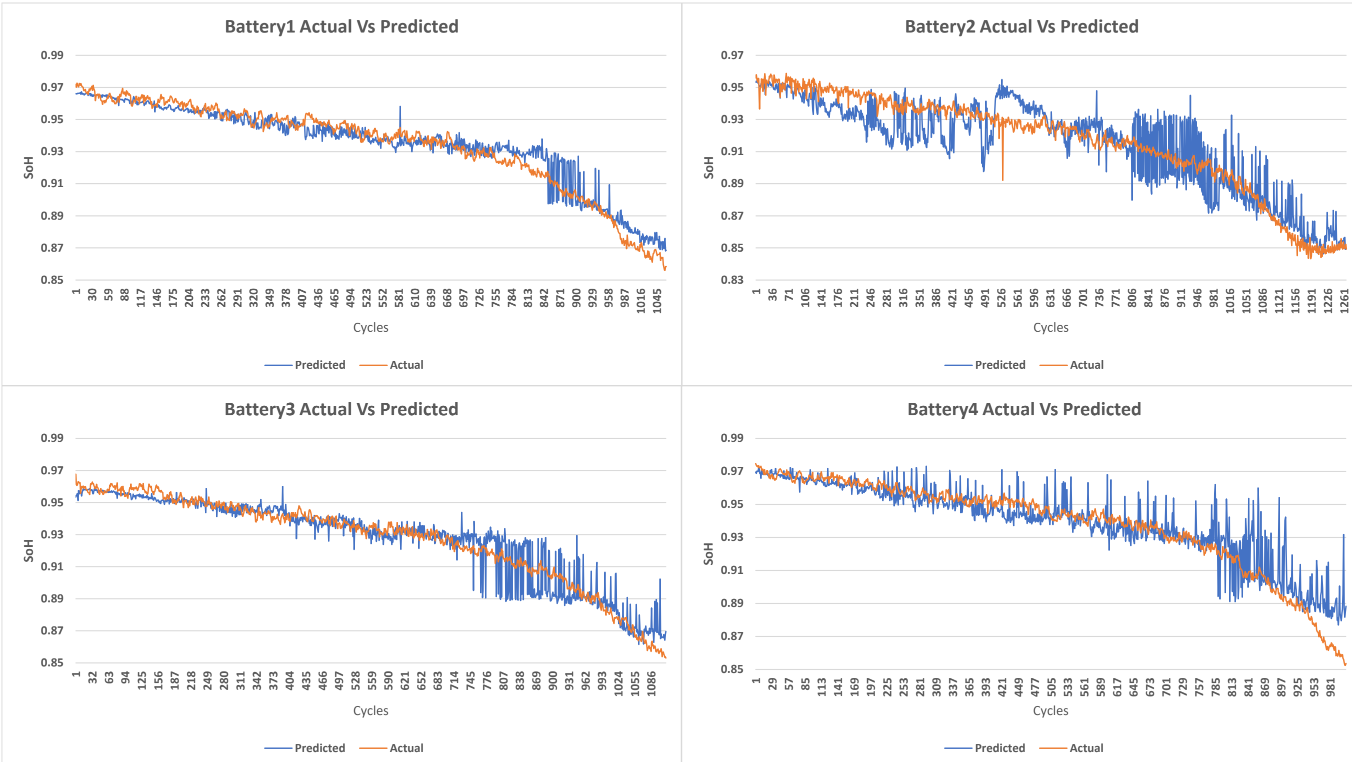

Fig. 3. Actual and Predicted SoH values of different batteries

Lithium ion battery. To achieve this we are using the LSTM model with one LSTM layer and one dense layer which is a lightweight model. The prediction of the SoH on different batteries is shown in Fig. 3.

D. Explainable AI

Most of the machine or deep learning models are black box in nature not allowing us to know which feature that have been extracted helps in prediction of the target variable with least possible error. XAI methods aim to increase transparency and comprehensibility, enabling users to comprehend the factors that impact model predictions.These generate explanations to enhance trust, ensure compliance with legal and ethical standards, detect biases, and promote fairness in decision-making. Rule-based approaches, feature importance analysis, local and global explanations, and visualizations are commonly used in XAI. To assess model interpretability, we are using Explainable AI.

E. Long Horizon Prediction

Long horizon battery prediction is the task of forecasting the future state of a battery over a long period of time, typically hours or days into the future. It is a challenging task that requires advanced machine learning techniques and domain-specific knowledge. This prediction can be crucial in a variety of applications, such as in electric vehicles, grid energy storage, and renewable energy integration. Deep learning techniques, particularly recurrent neural networks (RNNs), have been shown to be effective for long horizon battery prediction. RNNs are a class of neural networks that are designed to handle sequential data by processing each input in the sequence and maintaining an internal state or memory of previous inputs. This makes them well-suited for time series forecasting tasks, such as battery prediction. Therefore, we have used LSTM model and estimated upto 1000 cycles as shown in Fig 4.

IV. Results and Discussion

A. Comparison with different battery datasets

The best model from the above state of the art models i.e., Long Short-Term Memory Network (LSTM) is used as our final model which has been used on different datasets along with their performances was shown in Table II. Performance of LSTM model on different datasets is given by Table II.

TABLE II
Evaluation of SoH prediction for different batteries

Battery	RMSE	MAE
Battery 1	0.007	0.0052
Battery 2	0.0137	0.011
Battery 3	0.0084	0.006
Battery 4	0.011	0.0077

B. Long Horizon SoH prediction

Using the best performing model (LSTM network), Long horizon SoH prediction was carried out for different number of cycles i.e., for 60, 70, 80, 90, 100, 110, 120. Out of these

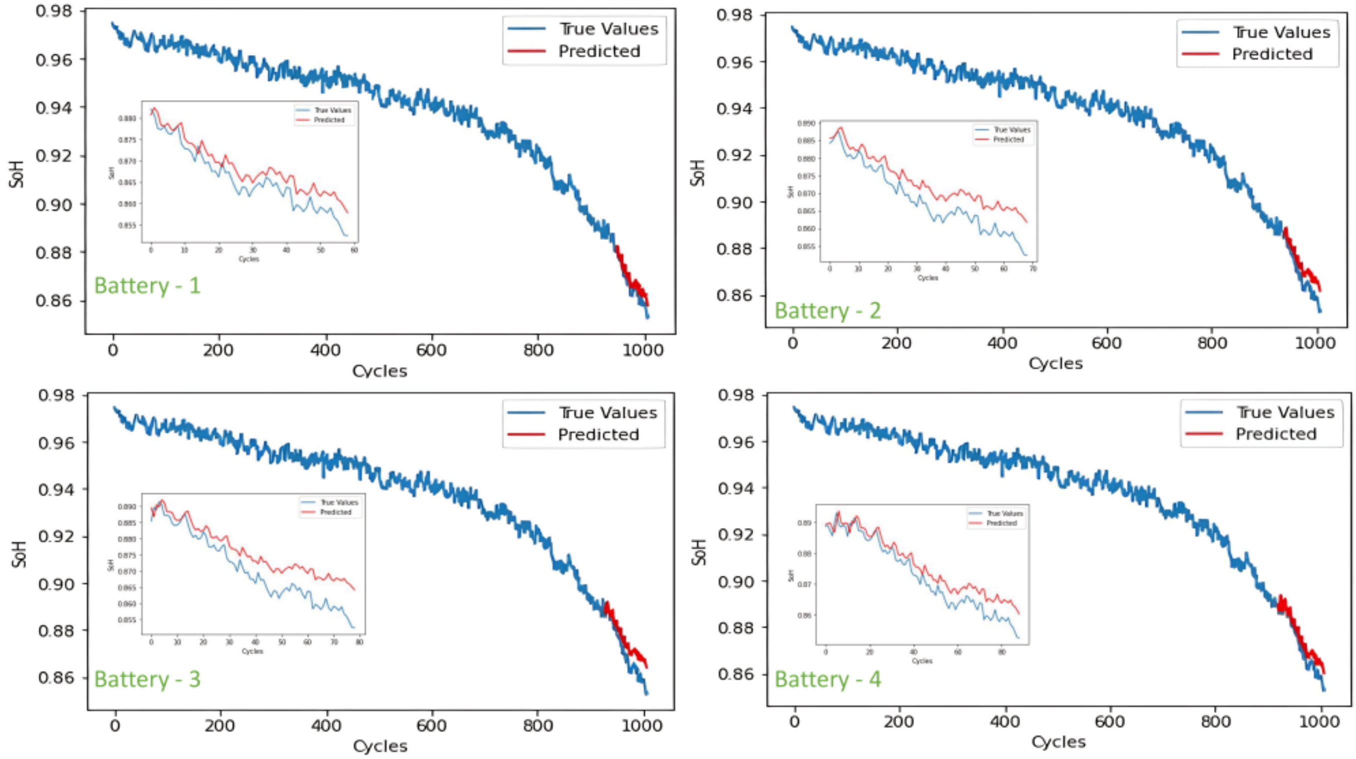

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Fig. 4. Long horizon Prediction on different batteries of Toyota Dataset.

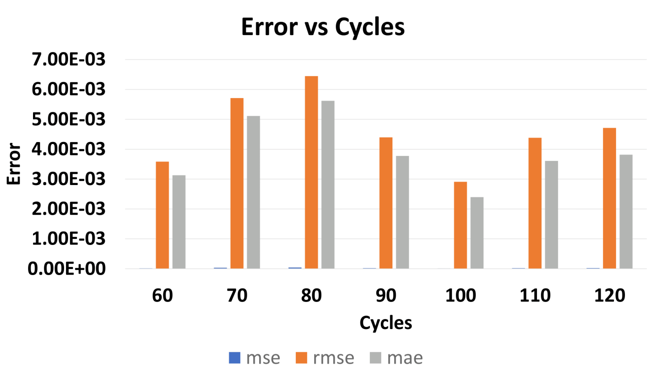

Fig. 5. Long horizon SoH prediction error for different cycles

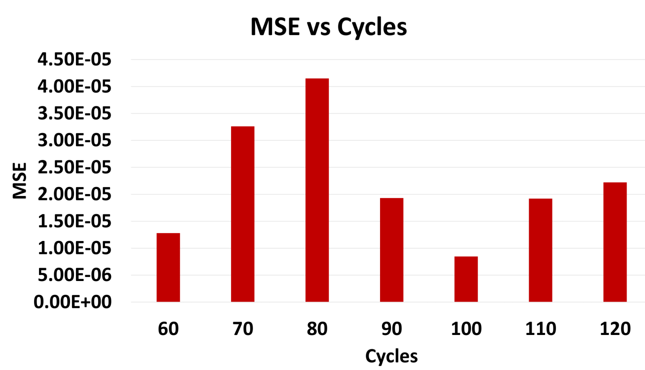

Fig. 6. Long horizon SoH prediction error (MSE) for different cycles

we can find that the least error is being predicted for 100 cycles. The performance of the LSTM model on different number of cycles are shown in the Table III. The values of MSE are very low. So they are plotted separately in Fig. 6. So it is clearly visible from both the graphs that is from Fig. 5 and Fig. 6 that the values of MSE, MAE and RMSE values are low when the number of cycles are 100.

C. Explainable AI

We have used LIME (Local Interpretable Model-Agnostic Explanations) a popular technique in the field of Explainable AI (XAI) that provides local explanations for individual predictions of machine learning models which aims to approximate the behavior of complex models by generating interpretable explanations at the instance level. The idea behind LIME is to perturb the input features of a specific instance and observe the resulting changes in the model's predictions. By sampling and weighting these perturbations, LIME constructs a simplified local model that approximates the original model's behavior around the instance of interest.

The Fig. 7 represents the explanation generated for one of the output cases. The figure tells us that, the predicted value is -10.43. This is the output before applying inverse transform to the output. The 1^{st} column and 2^{nd} column negatively effects

TABLE III
COMPARISON WITH DIFFERENT BATTERIES

Cycles	MSE	RMSE	MAE
60	0.000012	0.0035	0.0031
70	0.000032	0.0057	0.0051
80	0.000041	0.0064	0.0056
90	0.000019	0.0043	0.0037
100	0.000008	0.0029	0.0024
110	0.000019	0.0043	0.0036
120	0.000022	0.0047	0.0038

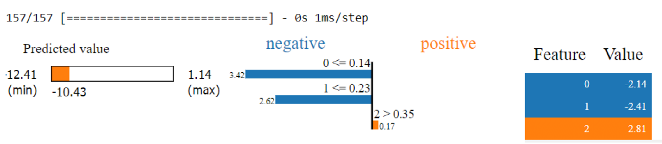

Fig. 7. Prediction model interpretation using Explainable AI.

the output by the 3.42 and 2.02 but where as 3^{rd} column positively effects the output variable by a value of 0.35. The feature and value of the corresponding row are as shown in the right most table in the Fig. 7. The 0, 1 and 2 feature name represents the 33^{rd} percentile, 66^{th} percentile and 99^{th} percentile values after scaling the values of the dataset.

D. Comparison with State of the art models

The feature that has been extracted was run different models and their evaluation metrics are shown above for the prediction of SoH. We can observe that deep learning models were performing well and among them LSTM is showing the best results. It is clearly evident from the Table IV that LSTM performs best when compared to other State of the Art model.

TABLE IV
COMPARATIVE ANALYSIS OF SOH PREDICTIONS

Model	RMSE	MSE
Linear Regression	0.233	0.174
Decision Tree Regression	0.425	0.2144
Artificial Neural Network (ANN)	0.0434	0.2115
Recurrent Neural Network (ANN)	0.0112	0.0812
Long Short-Term Memory Network (LSTM)	**0.005**	**0.0039**

V. CONCLUSION AND FUTURE SCOPE

Our proposed LSTM model has excelled in predicting battery State of Health (SoH) using the ITSSCV feature, showcasing minimal error. Its elegance lies in its simplicity, with just one LSTM and one dense layer, making it a lightweight and deployable alternative compared to complex models. Incorporating Explainable AI enhances interpretability, transforming it from a black-box to a white-box model. Moreover, it offers long-term SoH predictions for 100 cycles ahead. Future work includes designing an onboard battery health management system using Raspberry Pi, extracting better predictive features, and fortifying the model's resilience to varying parameters like temperature and load. These advancements highlight the model's novelty and promise in battery health management.

In summary, our LSTM model offers a simple yet powerful solution for SoH prediction, enhancing interpretability and enabling proactive battery health management, while future work focuses on further refinement and robustness.

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