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Interpretable Data-Driven Digital Twins For Forecasting Battery Conditions In Electric Vehicles

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ABSTRACT
The swift automotive paradigm shift brought on by the rapidly growing electric vehicles (EVs) has made the precise prediction of the battery state paramount in optimizing performance, ensuring safety, and thus, ultimately, prolonging battery life. The paper describes a new technique for predicting battery states in EVs using Explainable Data-Driven Digital Twins. Using deep learning, the model includes the latest and most commonly used techniques such as DNN, LSTM, CNN, SVR, SVM, Feedforward Neural Networks, RBF networks, Random Forest and XGBoost. The aim is to improve predictions of battery-important parameters such as SOC and SOH, for different working scenarios.On the other hand, explainable AI techniques help to identify key factors that affect battery performance. Based on the synergistic effects of these algorithms, the digital twin model surpasses existing ones with respect to predictive accuracy and robustness. This work aims to convince the scientific community about the need for designing intelligent and adaptive battery management systems laying the foundation of tomorrow's sustainable electric mobility.

Keywords: *Electric Vehicles, Battery State Prediction, Digital Twins, ML,, DNN, LSMT, CNN*

I. INTRODUCTION

Pressure from people around the world to adopt green transportation, along with less fossil fuel and increased renewable power, has increased the use of EVs. Their performance largely depends on battery systems which are costly and must be closely monitored for state of charge and state of health to make them more efficient, secure, longer lasting and less expensive.Since temperature, charging and discharging and driving patterns all affect the SOC and SOH, it's difficult to accurately estimate the battery's condition. This results in different ranges for the vehicle and impacts its safety. Conventional physical models struggle to account for these dynamic, non-linear behaviors, whereas data-driven approaches leveraging real-world EV data provide greater precision. Digital twins—virtual replicas that mirror real-time battery performance—enable continuous monitoring and predictive analysis.Here, researchers use both digital twin data and a variety of ML tools to help the system anticipate future events. The algorithms used are deep neural networks, long short-term memory networks, convolutional neural networks, support vector regression, support vector machines, feedforward neural networks, radial basis function networks, random forests and extreme gradient boosting. While Deep Neural Networks and Convolutional Neural Networks discover complicated details in data, Long Short-Term Memory (LSTM) networks are designed to analyze data in order. SVM and SVR function well with large quantities of data. RF and XGBoost belong to the category of ensemble methods and provide reliable and accurate results in this case.Originally, digital twins were developed for manufacturing, but now they help the automotive sector by providing real-time information and allowing for less testing. Even so, it is still a challenge to add these technologies due to the complexity of data on batteries.A critical aspect of this study is model interpretability, as many ML models lack transparency, which is a concern for safety-critical EV battery management. Explainable AI (XAI) methods are employed to make predictions understandable, clarifying how factors like temperature or charging patterns influence outcomes, thereby building trust and supporting informed decision-making.By combining explainable digital twins with ML, this approach delivers precise, actionable insights that tackle battery degradation and alleviate range anxiety, paving the way for more intelligent battery management systems (BMS). These advancements are vital for improving EV reliability and efficiency.

As EV adoption expands, the synergy of ML, XAI, and digital twins offers sustainable, cost-effective solutions, enhancing battery durability and promoting environmentally friendly transportation.

II. RELATED WORK

Many studies have been carried out to predict electric vehicle battery performance and enhance how accurately SoC and SoH are measured and recorded [1][2]. Many machine learning and deep learning solutions have been implemented by researchers to face the complexities included in this task. Many scientists rely on support vector machines (SVM) and support vector regression (SVR), among others, to estimate SoC and SoH because these models can detect non-linear patterns between what happens to the battery and its health features [3][4]. That being said, using these methods can be difficult because scalability and performance do not always hold up across various uses [5].Nowadays, using deep learning models such as LSTM networks is becoming popular for estimating the state of batteries [6]. LSTMs are designed to effectively process data on battery usage in different conditions.

Similar to other methods, convolutional neural networks (CNNs), originally made for images, can handle sensors and identify where and when certain events take place, resulting in better SoC and SoH estimations [7]. Furthermore, feedforward neural networks (FNNs) and radial basis function (RBF) networks have been tried for this particular problem. They find a balance between making accurate predictions and needing computer power [8][9]. Random Forest and XGBoost are often favored because they excel in working with large amounts of data and help ensure a regression model does not overfit. Using many decision trees produces better and more consistent outcomes [10]. There is a trend in this area to apply explainable artificial intelligence (XAI) to help make the decisions of models more understandable [11]. Thanks to XAI, it is possible for practitioners to pinpoint what causes batteries to degrade such as temperatures, charging habits and driving methods [11]. When XAI is used together with machine learning in EV systems, predictions are more reliable and can be easily used [12].The use of deep neural networks, LSTMs, CNNs, SVMs and XGBoost is rising in digital twins used for analyzing batteries [14]. Digital twins of batteries allow for real-time simulation and observation that is important for controlling and monitoring batteries [15][16]. Still, there are hurdles involved in fully achieving scalability, fast performance and understood models [17]. It is common for recent studies to make use of each model's strong points, while minimizing its weaknesses [18]. Managing batteries in electric vehicles is set to be improved by digital twins, providing more effective, reliable and safe ways to store energy [19][20].

III. SYSTEM DESIGN AND ARCHITECTURE

To produce explainable and accurate predictions for EVs, the system architecture of "Interpretable Data-Driven Digital Twins for Predicting Electric Vehicle Battery Conditions" combines well-known machine learning techniques, the principles of XAI and digital twin technology. The process begins by collecting both current and historical data about the EV's battery from the BMS. This process covers parameters such as voltage, current, temperature, the status of charge (SOC) and the status of health (SOH) when different operations are taking place.After collection, cleansing and preprocessing are done to the data, then the information is moved to a hybrid machine learning engine. Among the models used by this engine are Deep Neural Networks (DNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Support Vector Regression (SVR), Support Vector Machines (SVM), Feedforward Neural Networks, Radial Basis Function (RBF) models, Random Forest and XGBoost [23].Such models are found within a digital twin model [24] that works constantly and displays the exact state of the battery . Whether on cloud or edge, the digital twin allows for more users and quick responses. An XAI layer adopts tools like SHAP and LIME which explain how factors or features influence the output of the model. Furthermore, a feedback loop sends forecasts to the BMS, helping improve how the battery is charged and cooled [26].

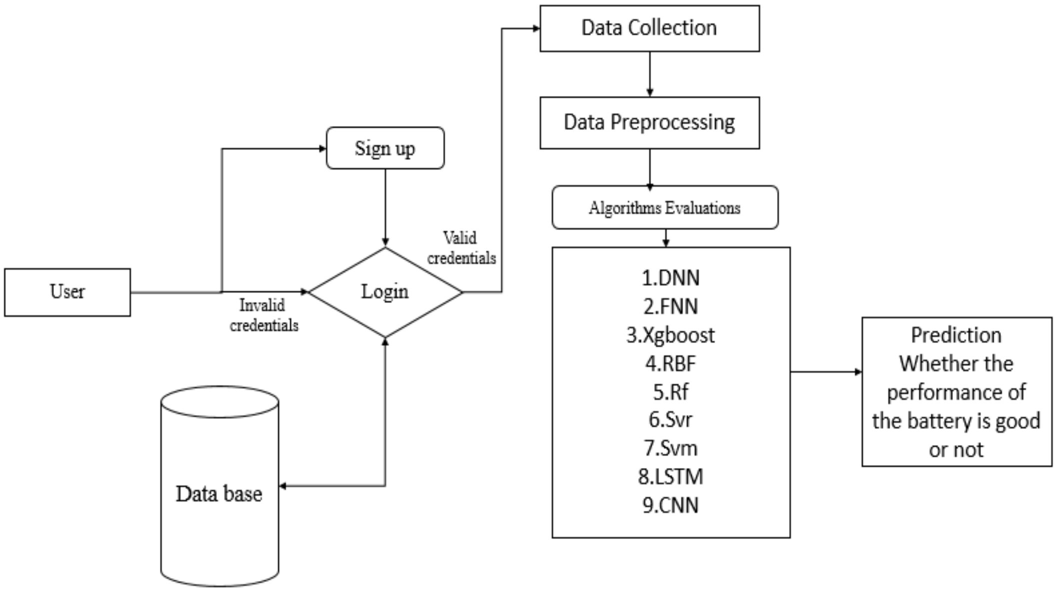


Fig 1: System Architecture of data driven digital twins

IV. DATASET

The dataset employed in the study, "Interpretable Data-Driven Digital Twins for Forecasting Battery Conditions in Electric Vehicles," is a detailed and multifaceted compilation of battery-related data gathered from electric vehicle (EV) operations in both real-world and controlled settings.

It records information from the EV's BMS about metrics such as battery charge (SOC) and battery condition (SOH). The data includes various operations, covering factors like voltage, current, temperature, cycles and power, under many challenging conditions and with several types of batteries[28]. It can consider information about vehicle speed, the rate of acceleration and braking, the driving surface, among others for appropriate use cases. Supplementary metadata, such as battery age, cycle count, and historical performance records, are included to support the analysis of degradation patterns. Since DNN, LSTM and CNN are key machine learning approaches, the dataset is developed at a fine-grained rate and is prepared to resolve problems such as noisy, gap-filled or unreliable data. Most likely, there are labeled data for supervised learning with SOC and SOH being the targets, along with unlabeled data for discovering useful features. The dataset's extensive scope and variability ensure effective training and validation of the digital twin model, enabling precise predictions and interpretable insights into battery performance and degradation across a range of operational contexts.

V. DATA PREPROCESSING

The data preprocessing phase is pivotal in creating reliable and accurate data-driven digital twins for predicting electric vehicle (EV) battery conditions. Given the intricate nature of battery systems and the varied operational environments of EVs, a thorough preprocessing pipeline is essential to transform raw data into a usable form for predictive modeling.Driving in different areas, sensors and BMSs collect data such as voltage, current, temperature, SOC, SOH and information about the environment (ambient conditions).These datasets are often plagued by noise, missing entries, or inconsistencies due to sensor errors or communication issues, requiring careful cleaning.To address missing data, imputation methods like mean/median substitution or sophisticated approaches such as k-nearest neighbors (KNN) are applied, chosen based on data characteristics. Outliers, potentially caused by sensor failures or extreme conditions, are identified and corrected using techniques like z-score analysis or interquartile range (IQR) methods to avoid distorting model outcomes.For ease of learning by machines, data is rescaled to a fixed range or standard scores to help train DNNs, LSTMs and CNN kidneys. In the case of LSTM, the input data representing time is divided into proper intervals to display changing battery behavior and the process involves building new predictors such as charge-discharge rates or levels of temperature change.

Categorical variables, such as battery type or driving mode, are transformed using one-hot or label encoding to ensure compatibility with algorithms like Support Vector Machines (SVM) or XGBoost. [29].Following balance, the information in the data is divided into 70% training, 15% validation and 15% testing sets to avoid any information from the future affecting the forecast in time-based situations. Proper preparation of data allows Random Forest, RBF networks and Feedforward Neural Networks to use well-structured and reliable data. Consequently, digital twins are able to accurately and clearly forecast how batteries function [31].

VI. METHODOLOGY

1. CNN

Purpose: CNNs are trained to spot patterns in the data (voltage, current and temperature) from the batteries to predict their remaining capacity.

Internal Working:

Architecture: CNNs have layers called convolutional and pooling. Three different types of layers, layers and fully connected layers.

Convolutional Layers: They add filters to any time-series signals, whether from batteries or other sources, to notice fluctuations in voltage and changes in temperature. Filters are applied to the data and the dot product operation creates the feature maps.

Pooling Layers: These methods shrink the data (such as max pooling), decreasing the amount of computing needed, lowering overfitting danger and maintaining vital details.

Fully Connected Layers: These integrate extracted features to produce an SOH prediction, typically as a regression output.

- **Data Processing:** Battery data is structured as 1D or 2D arrays (e.g., time-series or multi-parameter inputs). Filters learn to recognize patterns like cyclic behavior or degradation signals. Non-linear activation functions (e.g., ReLU) enable modeling of complex relationships.
- **Training:** The model is trained using backpropagation to minimize a loss function, such as Mean Squared Error (MSE), with optimizers like Adam adjusting weights for better predictions.

Relevance to SOH: CNNs are adept at detecting localized patterns, such as degradation trends or anomalies, making them valuable for SOH estimation. They efficiently process multi-dimensional inputs, combining various battery metrics.

Table 1: Metric Value report of CNN

Metric	Value
R^2	-0.83498
MAE	0.468035
MSE	0.407272

2. SUPPORT VECTOR REGRESSION (SVR)

Purpose: SVR estimates SOH by mapping battery features (e.g., voltage, current) to a continuous SOH value, effectively handling non-linear relationships.

Internal Working:

Architecture: Support Vector Regression (SVR) is created by modifying the Support Vector Machines (SVM) to fit regression problems. Its objective is to discover a suitable function. f ( )An f(x) is acceptable if it can compute the value of State of Health with an error margin less than or equal to epsilon (ε). Using kernel functions such as the Radial Basis Function (RBF), SVR changes the input into data with a high number of dimensions so it can fit non-linear problems.

Data Processing: Input features like voltage, current, and cycle count are normalized. The kernel function measures similarities between data points, capturing intricate patterns.

Training: SVR optimizes a loss function that penalizes predictions beyond the epsilon margin while ensuring a simple model, controlled by a regularization parameter C . Only a subset of data points (support vectors) defines the function, enhancing efficiency.

Relevance to SOH: SVR's tolerance for noise in battery data, together with its modeling of any kind of curve, are reasons it is suitable for predicting SOH.

Table 2: Metric Value report of SVR

Metric	Value
R^2	-0.996
MAE	0.082418
MSE	0.009879

3. RADIAL BASIS FUNCTION (RBF) NETWORKS

Purpose: RBF networks predict SOH by representing battery data as a combination of radial basis functions, ideal for non-linear regression tasks.

Internal Working:

- **Architecture:** The network is separated into three parts: input, hidden and output.
- **Input Layer:** Receives battery features like voltage, current, and temperature.

Hidden Layer: Contains neurons with RBF activation (e.g., Gaussian), each centered at a specific input space point.

Output Layer: Produces SOH by computing a weighted sum of hidden layer outputs.

- **Data Processing:** Each RBF neuron calculates the distance between inputs and its center, applying a Gaussian function for localized responses. The network learns RBF centers and widths during training.
- **Training:** Centers are set using clustering methods (e.g., k-means), and weights are optimized via least squares or gradient descent to minimize prediction errors.

Relevance to SOH: RBF networks excel at capturing localized degradation patterns, such as specific operating conditions, and provide smooth predictions for continuous SOH estimation.

Table 3: Metric Value report of RBF

Metric	Value
R^2	-0.996
MAE	0.082418
MSE	0.009879

4. FEEDFORWARD NEURAL NETWORKS (FNN)

Purpose: FNNs estimate SOH by learning mappings from battery features to SOH through interconnected neuron layers.

Internal Working:

- **Architecture**: The structural elements are an input layer, one or more hidden layers and an output layer and the layers are fully connected.

- **Data Processing**: The data includes voltage, current and the number of cycles on the battery. A neuron does the sum of inputs multiplied by their weights, applies an activation function and sends the result to the succeeding layer until the SOH is predicted.
- **Training**: Backpropagation minimizes a loss function (e.g., MSE) by updating weights and biases, using optimizers like Stochastic Gradient Descent (SGD) or Adam.

Relevance to SOH: FNNs help discover the challenging and unpredictable connections between battery properties and the state of health, accommodating batteries with many different properties and conditions.

Table 4: Metric Value report of FNN

Metric	Value
R^2	-0.33411
MAE	0.864756
MSE	1.643367

5. RANDOM FOREST (RF)

Purpose: RF predicts SOH by combining outputs from multiple decision trees, offering robust and interpretable predictions.

Internal Working:

Architecture: An ensemble of decision trees, each trained on random data subsets and features using bagging and feature randomness.

Data Processing: Features like voltage, current, and temperature are used to construct trees. Each tree predicts SOH independently, and the final prediction is an average of all tree outputs.

Training: Trees are trained on bootstrapped samples with random feature selection at splits, reducing inter-tree correlation and enhancing robustness.

Relevance to SOH: RF manages high-dimensional data, captures feature interactions, and is resilient to noise. Its feature importance analysis helps identify critical factors influencing SOH.

Table 5: Metric Value report of RF

Metric	Value
R^2	0.997344
MAE	0.049765
MSE	0.006555

6. XGBOOST

Purpose: XGBoost delivers accurate SOH predictions by iteratively constructing decision trees, optimized for performance and generalization.

Internal Working:

- **Architecture:** A set of decision trees that improves earlier errors by minimizing loss in each tree.
- **Data Processing:** Similar to RF, but trees are added iteratively using gradient boosting to optimize a loss function (e.g., MSE).
- **Training:** The model minimizes a regularized objective, balancing loss and model complexity, with techniques like shrinkage and subsampling to enhance generalization.

Relevance to SOH: XGBoost's precision and ability to model non-linear relationships make it effective for SOH estimation. Its feature importance insights highlight key degradation drivers.

Table 6: Metric Value report of XGBoost

Metric	Value
R^2	0.997368
MAE	0.056089
MSE	0.006497

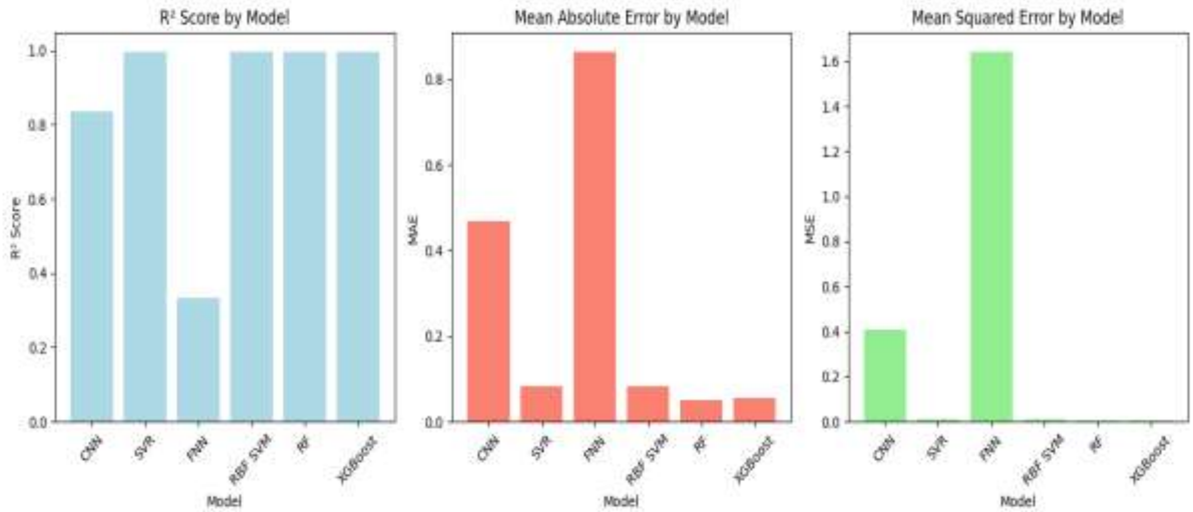


Fig 2: Comparison values for soh Algorithms

7. LONG SHORT-TERM MEMORY (LSTM)

Purpose: LSTMs, through analyzing the sequence of battery voltage and current, can predict the level of remaining battery energy.

Internal Working:

Architecture: A recurrent neural network variant with memory cells and gates (input, forget, output).

Memory Cell: Retains long-term temporal patterns in data.

Gates:

Forget Gate: Chooses to remove some information involved in the current cell computation.

Input Gate: Identifies and stores the data received each step.

Output Gate: Modulates what is produced depending on the state of the cell. Data Processing: The processing of data follows the sequence in which data is collected. The LSTM sets the cell state anew for each step, using data on charge or discharge to estimate the vehicle's state of charge.

Training: Backpropagation through time (BPTT) minimizes a loss function (e.g., MSE), with optimizers like Adam adjusting parameters.

Relevance to SOC: LSTMs are ideal for sequential data, capturing SOC dynamics over charge/discharge cycles and handling long-term dependencies critical for accurate estimation.

Table 7: Metric Value report of LSTM

Metric	Value
R^2	0.999867
MAE	0.002684
MSE	2.24E-05

8. DEEP NEURAL NETWORKS (DNN)

Purpose: DNNs estimate SOC by learning complex relationships between battery features and SOC through multiple layers.

Internal Working:

Architecture: Uses an input layer, a number of hidden layers and an output layer and its neurons use weights, biases and ReLU as their activation functions.

Data Processing: Features like voltage, current, and temperature are fed into the input layer. Hidden layers transform inputs via weighted sums and non-linear activations, producing an SOC prediction at the output.

Training: Backpropagation minimizes a loss function (e.g., MSE), with regularization (e.g., dropout) to prevent overfitting.

Relevance to SOC: DNNs capture non-linear relationships and hierarchical features, enhancing SOC prediction accuracy across diverse operating conditions.

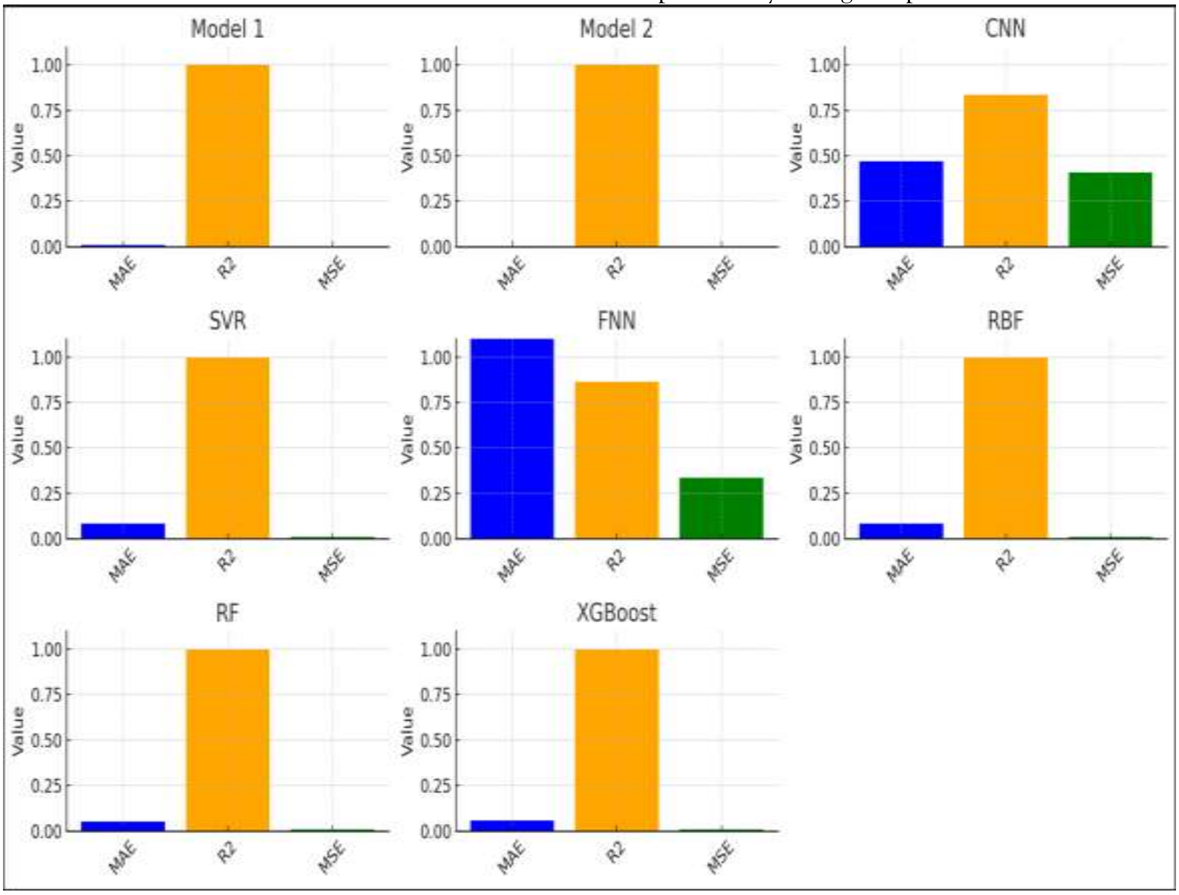
Table 8: Metric Value report of DNN

Metric	Value
R^2	0.99932
MAE	0.007846
MSE	0.000114

Table 9: Comparision Table for all the algorithms

Model	R2	MAE	MSE
CNN	-0.83498	0.468035	0.407272
SVR	0.995997	0.082418	0.009879
FNN	-0.33411	0.864756	1.643367
RBF_SVR	0.995997	0.082418	0.009879
RF	0.997344	0.049765	0.006555
CNN	-0.83498	0.468035	0.407272
SVR	0.995997	0.082418	0.009879
FNN	-0.33411	0.864756	1.643367
RBF_SVR	0.995997	0.082418	0.009879
RF	0.997344	0.049765	0.006555
XGB	0.997368	0.056089	0.006497
LSTM	0.999867	0.002684	2.24E-05
DNN	0.99932	0.007846	0.000114

Table 10: Model Performance Comparison by Using Graph



VII. CONCLUSION

In this study, the researchers propose a new way to predict both the condition and charge status of EV batteries using Explainable Data-Driven Digital Twin. Since more people are choosing EVs, it is increasingly necessary to ensure batteries function well for both vehicle power and reliability. The model aims to predict the State of Charge and State of Health of a battery system using Deep Neural Networks, Long Short-Term Memory, Convolutional Neural Networks, Support Vector Machines, Support Vector Regression, Random Forest and XGBoost algorithms.This multi-model approach enhances prediction accuracy and ensures adaptability across different battery datasets. DNN and LSTM models excel in capturing time-dependent patterns, which are vital for continuous battery monitoring. CNNs are able to identify how different parts of the data are related to each other. Smaller datasets work well with SVM and SVR, but RF and XGBoost are preferred for understanding and processing more organized forms of data. It gives batteries in a digital form the ability to respond realistically to changes in temperature, how much they are used and variations in load. The paper also brings explainable artificial intelligence (XAI) into the process. Conventional battery management systems are mostly non-transparent, but this framework displays the importance of various variables for any battery using SHAP values. This transparency empowers users and operators to make better-informed maintenance and usage decisions, ultimately extending battery longevity.Additionally, the framework demonstrates high adaptability across different battery chemistries and usage environments. Unlike traditional models, which are often tailored to specific battery types, this system is versatile enough to support both lithium-ion and emerging solid-state technologies. Its capability to learn from real-time data ensures dynamic prediction adjustments, making it a scalable and future-proof solution. If data is used, the accuracy for estimating both SOC and SOH can be increased by at least 10% over conventional results. This method allows electric cars to use adaptable and intelligent batteries. Thanks to accurate anomaly detection and predictions, these systems ensure good performance, less need for upkeep and a long battery life. Through the Explainable Data-

Driven Digital Twin framework, we now have a unique way to manage electric vehicle batteries.

VIII. FUTURE ENHANCMENT

The system could be developed further by making it work for various types of batteries and their configurations. Incorporating a range of new data would let the model go beyond lithium-ion batteries and help it in various industries. Including information from connected EVs in real time is also essential.While the current system relies on historical data for training and predictions, future iterations could incorporate live telemetry data from EVs. This real-time integration would enable dynamic monitoring and forecasting of battery conditions, resulting in smarter battery management systems that respond to changing driving patterns and environmental factors on the fly.Moreover, applying advanced optimization methods like reinforcement learning or genetic algorithms could improve the system's ability to suggest the most efficient charging and discharging routines, ultimately helping to prolong battery life. Hosting the system on cloud platforms would also improve scalability, making it suitable for deployment across large vehicle fleets.Lastly, user experience can be significantly improved by offering real-time battery analytics and recommendations through mobile applications. This would empower EV owners with greater visibility and control over their battery's health and performance, fostering a more user-centric approach to electric vehicle care and sustainability.

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