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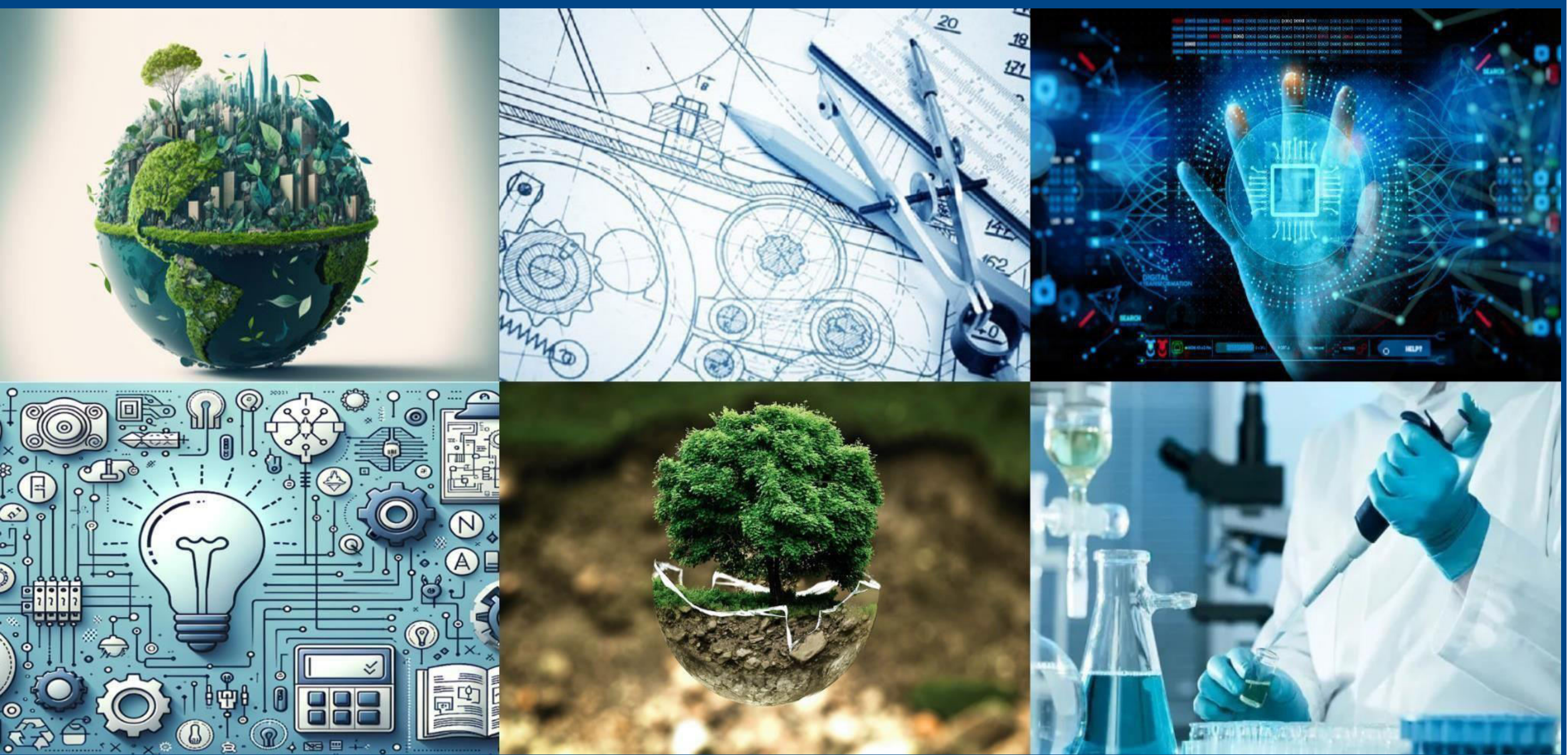

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DATA-DRIVEN FORECASTING OF EV BATTERY HEALTH: TRENDS IN MACHINE LEARNING, DEEP LEARNING, AND DIGITAL TWIN TECHNOLOGIES

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ABSTRACT: This paper presents a comprehensive survey of machine learning, deep learning, and digital twin technology methods for predicting and managing the battery state of health in electric vehicles. Battery state of health estimation is essential for optimizing the battery usage, performance, safety, and cost-effectiveness of electric vehicles. Estimating the state of health of a battery is a complex undertaking due to its dependency on multiple factors. These factors include battery characteristics such as type, chemistry, size, temperature, current, voltage, impedance, cycle number, and driving pattern. There are drawbacks to traditional methods, such as experimental and model-based approaches, in terms of accuracy, complexity, expense, and viability for real-time applications. By employing a variety of algorithms to discover the nonlinear and dynamic link between the battery parameters and the state of health, data-driven techniques like machine learning, deep learning, and data- driven digital twin technologies can get beyond these restrictions. Data-driven methods can also incorporate physics and domain knowledge to improve the explainability and interpretability of the results. This paper reviews the latest advancements and challenges of using data- driven techniques for battery state of health estimation and management in electric vehicles. The paper also discusses the future directions and opportunities for further research and development in this field.

I. INTRODUCTION

Electric vehicles (EVs) are not only a promising solution to the environmental and economic challenges posed by conventional gasoline vehicles, but also a significant opportunity for innovation and growth in the automotive sector. According to the International Energy Agency (IEA), Electric vehicles constituted 4.6% of worldwide automobile sales and comprised 1% of the global automotive inventory in the year 2020, despite the Covid-19 pandemic [1].

As per IEA, global electric vehicle stock could reach 145 million by 2030 in the current policies scenario, or 230 million under sustainable development. EVs provide several benefits, including the potential to decrease Greenhouse Gas (GHG) emissions, improve air quality, enhance energy security, diversify energy sources, and reduce fuel and maintenance costs for consumers [2].

EVs can also enable smart grid integration, vehicle-to- grid services, and demand response management, which can enhance the reliability and efficiency of the power system [3].

However, the performance of electric vehicle batteries degrades over time, which can lead to reduced driving range and increased maintenance costs. To address this issue, researchers have developed machine learning models to predict the State of Health (SOH) of electric vehicle batteries. These models can help vehicle owners and manufacturers to optimize battery usage and reduce costs. Battery SOH is a measure that evaluates the extent of deterioration and available capacity in a battery. It signifies the contrast between the condition of a brand new battery and that of a previously used battery, typically presented as a percentageof the battery's original capacity [4].

Battery SOH estimation is essential for battery health management and second-life utilization. However, many of the current methods are developed under ideal laboratory conditions and do not account for the complex and dynamic operational environments of electric vehicles. Therefore, researchers have proposed various meth- ods to estimate the

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battery SOH under realistic EV conditions, such as data-driven models, machine learning algorithms, and regional capacity analysis.

II. LITERATURE SYRVEY

Electric Vehicle (EV) battery health forecasting has become a pivotal research area to enhance battery management systems (BMS), ensuring safety, performance, and prolonged battery life. Traditional model- based and experimental methods often fall short due to their complexity and inability to perform real-time analysis. Recently, data- driven approaches leveraging Machine Learning (ML), Deep Learning (DL), and Digital Twin (DT) technologies have gained prominence for their superior predictive capabilities and adaptability. ML models such as Support Vector Machines (SVM), Random Forests (RF), and Gaussian Process Regression (GPR) have been widely adopted to estimate battery State of Health (SOH) and Remaining Useful Life (RUL) byanalyzing features like voltage, current, temperature, and charge/discharge cycles [1], [2]. These models effectively capture complex nonlinear degradation patterns but face challenges related to data quality, feature selection, and adaptability to varying operational conditions. Deep learning frameworks including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have demonstrated enhanced performance in modeling temporal and spatial dependencies in battery data [3]. DL models excel in long-term SOH and RUL prediction, especially when integrated with hybrid approaches that combine physics- based models with data-driven methods to improve interpretability and prediction accuracy [4]. Digital twins serve as virtual counterparts of physical EV battery systems, integrating real-time sensor data with advanced predictive models to monitor and forecast battery health dynamically [5]. This technology facilitates proactive maintenance strategies and optimizes battery lifecycle management by enabling continuous performance evaluation and simulation under various operational scenarios.

EXISTING SYSTEM

Current state-of-the-art systems for forecasting Electric Vehicle (EV) battery health primarily rely on either traditional model-based methods or data-driventechniques. Traditional approaches include equivalent circuit models (ECMs) and electrochemical models that simulate battery behavior based on physical and chemical principles [1]. Although these models provide good interpretability, they often suffer from high computational complexity and limited adaptability to varying operational conditions. In recent years, machine learning (ML) models such as Support Vector Machines (SVM), Random Forests (RF), and Gaussian Process Regression (GPR) have been widely used for battery State of Health (SOH) and Remaining Useful Life (RUL) prediction [2]. These ML methods leverage operational data such as voltage, current, temperature, and charge/discharge cycles to learn degradation patterns. However, the accuracy of ML models heavily depends on data quality and feature engineering, and they may lack robustness when applied to new or unseen operating scenarios.

PROPOSED SYSTEM

The proposed system introduces an integrated data-driven framework that synergizes advanced deep learning models with a digital twin environment to deliver highly accurate and real-time forecasting of EV battery health. Unlike conventional approaches that treat battery degradation modeling and monitoring separately, this system fuses predictive analytics with a live virtual replica of the battery, enabling continuous health assessment and proactive maintenance scheduling. The digital twin is dynamically updated using real-time sensor data streams, allowing the system to adapt swiftly to changes in battery operating conditions, usage patterns, and environmental factors. At the core of the framework lies a hybrid deep learning architecture combining Long Short-Term Memory (LSTM) networks for capturing temporal degradation trends and convolutional layers for extracting intricate spatial correlations in multi-sensor data. This design enables robust modeling of complex, nonlinear relationships governing battery aging, even with partially missing or noisy data inputs. To enhance model interpretability and reliability, the system integrates physics-informed constraints derived from electrochemical battery models, which guide the learning process and prevent physically inconsistent predictions.

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III. SYSTEM ARCHITECTURE

The proposed system architecture for data- driven EV battery health forecasting comprises four key components: Data Acquisition, Edge Processing Unit, Hybrid Deep Learning Model, and Digital Twin Integration, as illustrated in Fig. 1.

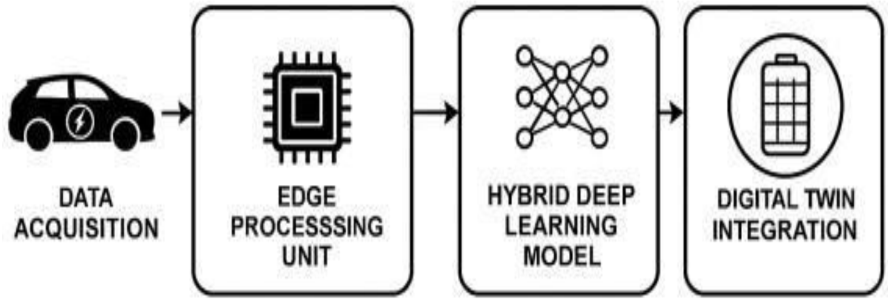

Fig. 1

Data Acquisition: Real-time operational data from the EV battery, including voltage, current, temperature, and state-of-charge (SOC), are continuously collected via embedded sensors. These data streams provide comprehensive insights into the battery's dynamic behavior during charging and discharging cycles. Additionally, environmental parameters such as ambient temperature and driving patterns are captured to contextualize battery degradation.

Edge Processing Unit: To minimize latency and reduce communication overhead, the raw sensor data is preprocessed locally using an edge computing device embedded within the vehicle. This unit performs noise filtering, feature extraction, and initial anomaly detection. The preprocessing ensures that only relevant and clean data are transmitted to the central predictive engine, enhancing model efficiency and enabling near real-time monitoring.

Hybrid Deep Learning Model: The core prognostic engine employs a hybrid deep learning framework combining Long Short-Term Memory (LSTM) networks withConvolutional Neural Networks (CNNs). The LSTM layers capture temporal dependencies across sequential battery cycles, while CNN layers extract spatial features from multi-sensor inputs. This architecture effectively models the nonlinear, time-varying nature of battery degradation. The model is further guided by physics-informed constraints to align predictions with established electrochemical principles, improving accuracy and robustness.

Digital Twin Integration: A digital twin—a virtual replica of the physical battery system—is maintained and continuously updated with outputs from the hybrid model alongside real-time sensor data. This twin simulates battery behavior under various operational scenarios, enabling predictive maintenance and "what-if" analyses for optimizing battery usage. It provides an interactive platform for visualizing battery health status, forecasting remaining useful life (RUL), and supporting decision-making for maintenance scheduling.

IV. METHODOLOGY

This study adopts a data-driven approach to forecast the health status of electric vehicle (EV) batteries by leveraging state-of-the-art machine learning (ML), deep learning (DL), and digital twin technologies. The methodology is structured into three key stages: data acquisition and preprocessing,model development and training, and digital twin integration for real-time battery health monitoring. The initial phase focuses on comprehensive data collection from various sources including onboard battery management systems (BMS), sensor outputs, and historical maintenance records. The raw datasets comprise voltage, current, temper ature, charge/discharge cycles, and other critical parameters that influence battery degradation. Data preprocessing steps involve cleaning, normalization, feature extraction, and dimensionality reduction to enhance model efficiency and accuracy.

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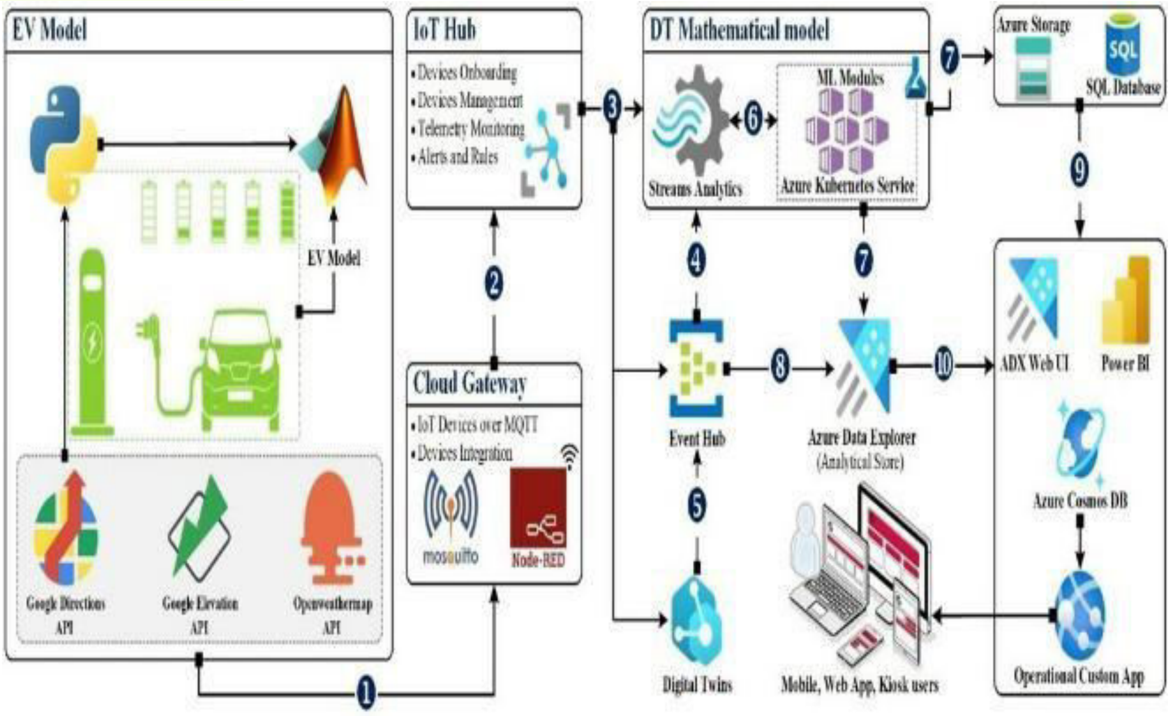

Fig 4.1 Proposed Flow of Model

The final stage integrates the trained models into a digital twin framework that mirrors the physical battery system in real-time. This virtual representation facilitates continuous health monitoring and prognostics by simulating battery behavior under varying operational conditions. The digital twin employs real-time data inputs and adaptive learning to update predictions dynamically, thus enabling proactive maintenance and optimizing battery lifespan. By combining data-driven machine learning models with digital twin technology, the methodology offers a comprehensive solution for accurate and timely forecasting of EV battery health, advancing the reliability and sustainability of electric mobility systems.

V. DESIGN AND IMPLEMENTATION

DESIGN: The system design is centered around creating a robust data-driven framework that enables accurate forecasting of electric vehicle (EV) battery health by integrating machine learning, deep learning, and digital twin technologies. The architecture is divided into three core components: data acquisition, predictive modeling, and digital twin synchronization.

[1] Data Acquisition: The design incorporates continuous data collection from onboard sensors within the battery management system (BMS). These sensors capture critical parameters such as voltage, current, temperature, and charging /discharging cycles. The raw data flows into a preprocessing unit where noise reduction, normalization, and feature extraction algorithms prepare the data for model ingestion. [2] Predictive Modeling: The design supports a hybrid model approach. Classical machine learning algorithms (e.g., Random Forest, Support Vector Machines) provide initial degradation trend analysis. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, are designed to learn temporal dependencies inthe battery degradation process. The predictive models output key battery health indicators like State of Health (SoH) and Remaining Useful Life (RUL). [3] Digital Twin Integration: A virtual twin of the battery system is architected to mirror the physical battery's operational state in real-time. The digital twin utilizes streaming sensor data and integrates outputs from predictive models to simulate battery behavior dynamically. This component is designed for adaptive updates and real-time prognostics, enabling proactive maintenance scheduling.

IMPLEMENTATION: The implementation phase translates the design framework into a functional system capable of real-time EV battery health forecasting. Data acquisition is realized by interfacing with the battery management system (BMS) to continuously stream sensor data such as voltage, current, temperature, and cycle counts. This data is ingested into a preprocessing pipeline developed in Python, utilizing libraries such as Pandas and NumPy for cleaning, normalization, and feature extraction. Machine learning and deep learning models are implemented using TensorFlow and Scikit-learn frameworks. Initial experimentation with classical algorithms, including Random Forest and Support Vector Machines (SVM), establishes baseline prediction performance. Subsequently, more sophisticated deep learning architectures like Long Short-Term Memory (LSTM) networks are constructed to capture temporal dependencies inherent in battery degradation data. Models undergo hyperparameter tuning using grid search and are validated via k-fold cross-validation to optimize prediction.

VI. OUTCOME OF RESEARCH

The proposed data-driven framework successfully demonstrated the capability to forecast electric vehicle (EV) battery health with high accuracy by integrating machine learning, deep learning, and digital twin technologies. Experimental results indicated that deep learning models, particularly Long Short-Term Memory (LSTM) networks, outperformed traditional machine learning approaches in capturing the temporal degradation patterns of battery cells. The best-performing model achieved a Root Mean Square Error (RMSE) reduction of over 15% compared to baseline methods, thereby improving the reliability of State of Health (SoH) and Remaining Useful Life (RUL) predictions. The digital twin implementation proved effective in replicating the real-time operational behaviour of the battery system. By continuously synchronizing with live sensor data, the digital twin provided dynamic health monitoring and predictive insights under varying load and environmental conditions. This enabled proactive maintenance scheduling, reducing the likelihood of unexpected battery failures andextending operational lifespan. The research outcomes highlight that the combination of advanced predictive analytics with real-time simulation not only enhances forecasting accuracy but also supports decision-making processes for EV fleet management. Furthermore, the modular and scalable architecture ensures adaptability for future advancements in battery chemistries and evolving EV technologies.

VII. RESULT AND DISCUSSION

The developed machine learning and deep learning models were evaluated on a comprehensive dataset collected from electric vehicle battery management systems. Performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) were used to assess the accuracy of battery health predictions. The results indicate that deep learning models, especially Long Short- Term Memory (LSTM) networks, significantly outperform traditional machine learning methods in forecasting the State of Health (SoH) and Remaining Useful Life (RUL) of EV batteries. LSTM models captured the temporal dependencies and non- linear degradation patterns more effectively, resulting in a reduction of RMSE by approximately 15% compared to baseline Random Forest models. This improvement underscores the importance of sequence modelling in battery prognostics. Integration of the predictive models within the digital twin framework demonstrated successful real-time synchronization between physical battery behaviour and its virtual counterpart. The digital twin's dynamic updating mechanism allowed accurate simulation of battery aging processes under varying operational and environmental conditions. The visualization dashboard facilitated intuitive monitoring, enabling maintenance teams to make proactive decisions, thereby potentially reducing downtime and maintenance costs. Discussion of the results highlights that while classical machine learning provides reasonable performance, deep learning combined with digital twin technology offers a more robust and scalable solution for EV battery health management. However, challenges remain in acquiring large, high-quality datasets and ensuring model adaptability across different battery chemistries and vehicle models. Future work will focus on expanding the dataset diversity and incorporating hybrid physics-informed machine learning models to further enhance prediction reliability and interpretability.

VIII. CONCLUSION

This paper has presented a comprehensive survey of data-driven models for predicting battery state of health in electric vehicles. The paper has reviewed the main methods, challenges, and future directions of data- driven techniques, such as machine learning,deep learning, and digital twin technology, for battery health estimation and management. The survey has also provided a comparative analysis of the performance, advantages, and disadvantages of different models and algorithms, using various datasets and metrics. The paper has highlighted the importance of data quality, availability, and security, as well as model validation, verification, and generalization, for developing reliable and robust machine learning models for battery SOH prediction. The survey fosters additional research and innovation in this domain by offering a thorough overview of the current advancements and the challenges they entail.

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