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An Intelligent Hybrid Machine Learning Model for Proactive Management of EV Battery Health and Lifecycle

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Highlights of the Study

- Hybrid Deep Learning Framework: The study introduces SmartBatt-HML, a novel hybrid model combining CNN, Bi-GRU, attention mechanisms, and XGBoost to achieve highly accurate EV battery health state classification and lifecycle prediction.
- Superior Predictive Accuracy: The proposed model achieves a state-of-the-art accuracy of 97.19% in SOH classification and demonstrates outstanding RUL prediction capability with a low RMSE of 3.74, outperforming conventional deep learning and ensemble models.
- Robust Feature Interpretation: By integrating electrochemical signature-based features such as IC curves, DVA peaks, and internal resistance, the model delivers enhanced interpretability and reliability for battery diagnostics across multiple health classes.
- Real-Time and Scalable Implementation: With an average inference time of 19.0 ms, SmartBatt-HML supports real-time deployment in BMS environments, making it suitable for embedded systems and scalable across diverse EV platforms.

Abstract

The rapid advancement in electric vehicle (EV) technologies necessitates the development of intelligent systems for monitoring battery health and forecasting lifecycle trends to ensure safety, efficiency, and operational longevity. This paper introduces SmartBatt-HML, a predictive health-based intelligent hybrid deep learning framework to be utilized in EV battery predictive health monitoring and optimizing the battery lifecycle. The given architecture is synergetically enhanced with a Convolutional Neural Network (CNN) to extract spatial features and a Bidirectional Gated Recurrent Unit (Bi-GRU) to learn temporal degradation models, attention mechanism to weigh specific cycles selectively, and XGBoost classification model that is more robust to make decisions. The model accepts multi-parameter time-series data on the battery cell voltage, current, temperature, state-of-charge (SOC) and internal resistance, as well as derived electrochemical degradation signatures like incremental capacity (IC) and differential voltage (DVA) scan. The experiments performed on benchmark battery datasets confirm the high performance of the model with classification accuracy, precision, recall, and F1-score equal to 97.19%, 96.85%, 96.92%, and 96.88% respectively. Moreover, SmartBatt-HML accomplishes superbly in Remaining Useful Life (RUL) forecast with Root Mean Square Error (RMSE) score of only 3.74 and Mean Absolute Error (MAE) score of 2.95. Its latency of 19.0 ms also supports the fact that it is ready to be deployed in embedded battery management systems that require real-time inference capability. In this study, the SmartBatt-HML methodology improves both accuracy of prediction and interpretability and scalability to real EV settings. The combination of hybrid architectures and sophisticated feature engineering promises to transform SmartBatt-HML into an excellent tool in the future of battery diagnosis and predictive maintenance policies.

Keywords- Electric Vehicle Batteries, State of Health, Remaining Useful Life, Hybrid Deep Learning, CNN, Bi-GRU, Attention Mechanism, XGBoost.

1. Introduction

The rising popularity of electric vehicles (EVs) is reshaping the transportation sector around the world due to the issues of environmental sustainability, and the need to shift towards clean energy sources worldwide. The EVs have their main focus on the battery mostly the lithium-ion battery systems that store energy, supply power to a car and also provide the car range. The safety, cost-effectiveness, and performance of EVs are directly associated with the life and service of their batteries [1] [2]. Nonetheless, batteries are normally prone to wear-out because they degrade prematurely when exposed to an electrochemical aging effect, mechanical deformity, and thermal fluctuations thereby undermining their capacity, power delivery, and general stability. As a result, smart battery health analysis and predictive maintenance have become important parts of Battery Management Systems (BMS), the ability to reliably track and maintain the battery's State of Health (SOH) and reliably predict the Remaining Useful Life (RUL). The 1E techniques are most typical in conventional means of battery health estimation; they include equivalent circuit modelling (ECM), electrochemical impedance spectroscopy (EIS), and capacity measurement methods [3] [4]. Although such methods provide an indication to the internal behaviour of the battery, they can be explained by difficult modelling assumptions, frequently involve a lot of calibration demands, and they are sensitive to environment standards. Additionally, those models might not generalize to other battery chemistries, usage profiles, and operating conditions. Since EVs are present in very diverse and dynamic real world environments, there is an urgent need of data-driven and adaptive models that are able to learn degradation trends autonomously based on the multi-sensor time-series data. Figure 1 illustrates some essential components of EV batteries.

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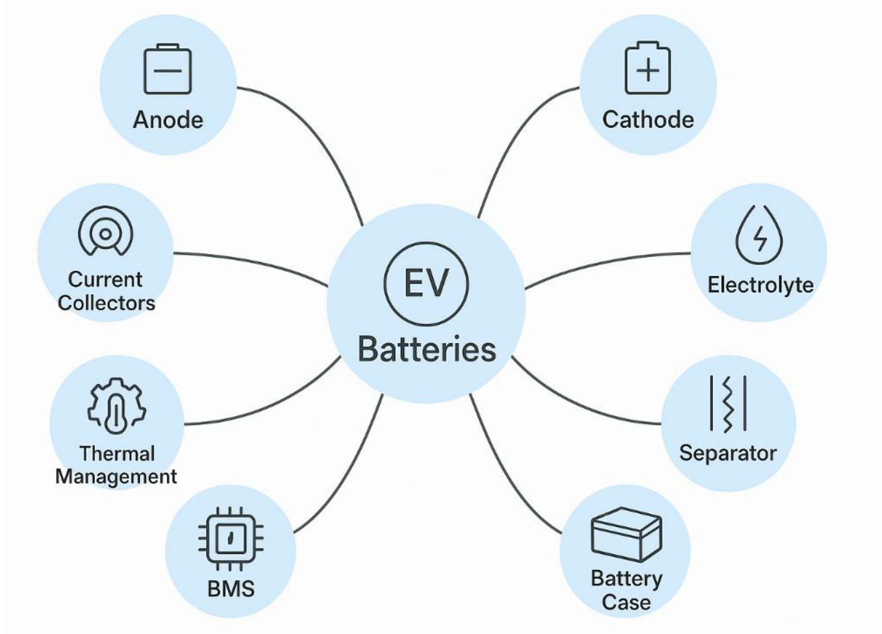

Figure 1. Components in Electric Vehicle (EV) Batteries

The recent breakthroughs on artificial intelligence (AI), deep learning in particular, have motivated the construction of potent models of battery SOH profiling and RUL prognostication [5] [6]. RNNs, LSTM networks and GRUs are architectures that have been employed to describe the dynamics of temporal relations of battery behaviour. In a similar pattern voltage and current profiles of the current profiles have been shown to benefit in extraction of local degradation features using Convolutional Neural Networks (CNNs). Robust classification on imbalanced data and noise has also been done using ensemble-based combinations such as XGBoost and Random Forests [7] [8]. Although these developments are impressive, single deep learning, or machine learning models are subject to limitations, in and of themselves. Although RNN-based architectures have succeeded in sequence modelling, they can experience driving gradients when modelling long cycles, and are not interpretable. CNNs, despite their efficacy in feature extraction, do not have memory mechanism needed in distinguishing the long-term trend on degradation [9] [10].

To overcome these limitations, this paper proposes SmartBatt-HML, which is a new hybrid model that combines Convolutional Neural Networks (CNN), Bidirectional Gated Recurrent Units (Bi-GRU), an attention mechanism, and an XGBoost classifier to facilitate precise, interpretable and real-time battery health. The CNN module will extract spatial patterns on the input signals like the voltage drop and current surges that is an indicator of localized degradation. The Bi-GRU module learns complex degradation patterns and temporal system dynamics and learns long-range temporal correlations in battery cycle data. The selective weighting attention mechanism considers the significant most important elements in the key time steps and cycles that help the model concentrate on appropriate memory (degradation) signature and disregard noise. Lastly, a decision layer in the form of an XGBoost model is used to incorporate deep learned feature representations learned along with feature importance-based classification on strong and interpretable predictions.

1.1 Research Motivation

Battery health monitoring is the key to safe and sustainable transportation of electric vehicles (EV). With the rise of EVs in the world, it has come to be of paramount importance that the right and proactive diagnostics of batteries be performed. Batteries are both expensive and sensitive to safety, and therefore, they are susceptible to degradation and unexpected failures, which occur in form of economic losses and performance deterioration or hazardous situations. The common diagnostic method commonly fails in the field because of additional usage and temperature restrictions. The proposed research is driven by the idea of having a real-time, intelligent system based on artificial intelligence that would predict battery health and service life to make more intelligent and more reliable battery management systems, which would operate EVs.

1.2 Significance of the Study

A smart battery management is the future of transportation, especially when it comes to lithium-ion systems. The given study introduces SmartBatt-HML, a hybrid deep learning framework that is aimed at predicting the degradation of EV battery and facilitating the battery lifecycle optimization. It is extremely fit to be used in the emerging EV ecosystems because it is interpretable, accurate, and feasible in real time. With rising adoption, the stakeholders will need to have scalable diagnostic tools that can be used in a multi-chemistry and multi-usage environment. In the near future, predictive maintenance can become the regulatory trend to secure safety and efficiency. SmartBatt-HML fills this gap and provides a powerful, deployable technology, meeting the challenges of AI-based innovation in energy storage and transportation environments to satisfy the required need.

1.3 Problem Statement

Current strategies on EV battery health monitoring are not sufficient, since they lack a coherent, scalable, and precise framework that is directly applicable in the challenges of real-life mobility. Conventional electrochemical models are ungeneralizable since they are too rigid, whereas numerous data-driven models separate the SOH categorization or the RUL regression and lack mutual explanatability. Further, these models also often disregard important degradation signs such as, Incremental Capacity (IC) and Differential Voltage Analysis (DVA) curves, and resort to plain sensor values. Deep learning models tend to be powerful yet not transparent and hence not efficient on real time applications. This paper introduces the SmartBatt-HML, which is a hybrid model that can combine SOH and RUL prediction with interpretability and the possibility to make the model run in the real-time.

1.4 Recent Innovations and Challenges

The latest development in electric mobility goes in terms of AI-powered advancements that help diagnose battery health. Such methods as RNNs, Transformers, and GNNs had been used to model battery degradation, and an increasing degree of interest is in combining electrochemical characteristics and attention mechanisms to achieve improved interpretability. But these developments have liabilities. A lot of models do not have a good generalization to the other chemistries of batteries or to conditions of the real world. Architectures that perform well usually require a large amount of data and processing power thereby being inappropriate in embedded BMS applications. Also, the deployment and explainability of this problem are essential issues in real-time. In response to this study, we propose SmartBatt-HML; a lightweight but powerful mixed model with the optimal tradeoff between speed, accuracy and interpretability in the practical integration of EVs.

1.5 Key Contribution of the study

- Development of a Hybrid Deep Learning Framework: The researchers present SmartBatt-HML, a new hybrid framework that combines synergistically CNN, Bi-GRU, and attention mechanisms as well as XGBoost to comprehend the space-time battery deterioration tendencies.
- Incorporation of Domain-Specific Features: The model utilizes engineered domain electrical parameters like Incremental Capacity (IC) traces, Differential Voltage Analysis (DVA) as well as the trend in inner resistance that take advantage of easier interpretation and fidelity of degradation signals.
- Attention-Based Cycle Weighting Mechanism: Custom attention layer is also adopted to dynamically assign the weight to battery charge/ discharge cycles to enable the model to concentrate on the degradation-decisive parts of long time-series data.
- Unified SOH and RUL Prediction Architecture: In contrast to the conventional systems where classification and regression are two separate tasks, SmartBatt-HML offers a combined predictive pipeline of predicting State of Health (SOH) and Remaining Useful Life (RUL).
- Optimized for Real-Time Deployment: The architecture is both lightweight and inference-efficient to make it applicable in real-time embedded Battery Management System (BMS) and on-board diagnostics in electric vehicles.

1.6 Rest of Section of the Study

The rest of the paper is organized as follows: Section 2 provides related studies about battery health estimation, machine learning-based SOH/RUL prediction models, and recent advances in hybrid deep learning frameworks for degradation diagnostics. Section 3 details the proposed methodology, outlining data preprocessing, feature engineering, hybrid model architecture design, and the integrated prediction pipeline of SmartBatt-HML. Section 4 describes the results and discussion, presenting performance comparisons, confusion matrices, RUL estimation accuracy, inference efficiency, and feature importance analysis. Finally, the conclusion and future scope in Section 5 summarize key findings and outline potential enhancements for real-world deployment and cross-chemistry scalability.

2. Related Works

Lithium-ion batteries (LIBs) have caused the fast development of electric transportation, which required advanced battery management systems (BMS) to achieve the safety and efficiency of transportation. Some major functions of BMS concern state monitoring and temperature. The rest have two fundamental areas of LIB health namely: state of health (SOH) prediction and remaining useful life (RUL) estimation. Correct SOH and RUL predictions increase battery life and maximize the performance [11]. The critical role of machine learning (ML) is to enhance the accuracy of prediction with the smallest complexity. The research provides a background to existing studies, issues, and values, as well as AI-based solutions on the improvement of LIB monitoring, supplementing the sustainable increase in electric vehicles.

A new approach of advanced condition monitoring of lithium-ion batteries (LIBs) in electric vehicle (EV) is proposed based on the digital twin (DT) technology that does not necessitate additional hardware or sensor calibrations. The DT system can be interfaced with the existing battery management system (BMS), and this makes it possible to monitor it in real-time [12]. It is a synchronization of IoT infrastructure in the cloud and offline modeling with the help of a long short-term memory (LSTM) algorithm, which is optimized to perform state-of-charge (SOC) predictions. Among the innovations, the method to produce synthetic data using a time-series generative adversarial network (TS-GAN) is worth mentioning to deal with the shortage of real-time data. This will enhance sustainability in energy management by batteries in terms of safety, efficiency, and lifespan.

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The study introduces an advanced battery management system (BMS) designed for real-time monitoring and analysis of an NCA 18650 4S lithium-ion battery (LIB) pack under high C-rate testing conditions. The BMS continuously tracks key parameters—voltage, current, and temperature—and integrates deep learning to estimate discharge capacity and predict the battery's state of health (SOH) [13]. Two experiments were conducted: a static test for validation and an in operando test on an electrically propelled vehicle. The system accurately reflected real-world behavior, with surface temperatures peaking at 55 °C and a mean capacity deviation of just 0.04 Ah, demonstrating high predictive accuracy and reliability.

The latest achievements of electric vehicles (EVs) are summarized, with the main ideas that the artificial intelligence (AI) plays crucial part in enhancing the battery management systems (BMSs) and control technology. Traditional techniques can be trounced by AI techniques such as machine learning (ML), neural networks (NNs), and reinforcement learning (RL) that are much more successful at enhancing battery state of health (SOH), state of charge (SOC), thermal management [14]. Artificial intelligence powered control systems can also increase energy distribution, regenerative brake, and power control during the differing driving situations. Predictive maintenance and fleet optimization are enabled using the integration of the Internet of Things (IoT) and big data. To sum up, the present review highlights the revolutionary effect of AI on the future of efficient, smart EVs.

The review looks into how the applications of data-driven methods in predicting, monitoring, and optimizing battery performance and health have increased in complex and stochastic environments. Conventional techniques of experimental and simulation techniques usually fail to cope with nonlinear electrochemical trends, and therefore, data-oriented approaches are vital [15]. The article gives the updates on the combination of theory models, experimentation tools and electrochemical testing performance within the data-driven approaches. It deliberates on the usage in the battery lifecycle: battery design and production, battery reuse and recycling and data extraction, model deployment and analytics. Lastly, it also answers critical issues and possible ways of scaling data-driven methods to industrial practices in next-generation batteries.

The study looks at the performances of different machine learning (ML) algorithms in regards to the Battery Health Analysis (BHA) assessment on predicting Remaining Useful Life (RUL). Three networks are compared, namely, Logistic Regression (LR), a Convolutional Neural Network (CNN), and a CNN optimized with the help of Particle Swarm Optimization (PSO) [16]. The evaluation is presented by the RMSE, MAE and R parameters. Although CNN is much better than LR (RMSE: 20.11, MAE: 15.26, R 2: 0.996), even further improvement can be achieved by using PSO-optimized CNN (RMSE: 14.97, MAE: 8.03, R 2: 0.998). These results suggest an opportunity of ML and optimized deep learning models in the battery management of EVs, renewables and electronics.

The paper analyses main aspects of the battery technology with an emphasis on the lithium-ion, lead-acid and nickel metal hydride (NiMH) batteries. It examines the production and how it is highly emphasized in increasing the performance of batteries [17]. Battery fault detection is also of concern, which is why early detection of issues through artificial intelligence (AI) as well as machine learning (ML) methods is useful in the study. In addition, it explores some of the available battery recycling procedures, namely pyrometallurgy, hydrometallurgy, mechanical separation, and electrodialysis and weighs environmental impact of these sorts of processes. Based on such in-depth discussion, the paper presents the technological evolution and sustainability interest of batteries, and the significant role of batteries in current energy systems.

The authors have developed an efficient model to anticipate Remaining Useful Life (RUL) of Nickel Manganese CobaltLithium Cobalt Oxide (NMC-LCO) batteries, which is one of the main issues associated with the use of electric vehicles (EVs) because the battery wearout is limited [18]. With the support of one of the datasets by Hawaii Natural Energy Institute (with more than 1,000 charge-discharge cycles of 14 batteries) the research adheres to some formal steps of data preprocessing, feature selection, and outlier removal. Several machine learning algorithms, which include the XGBoost, LightGBM, Cat Boost, Extra Trees Regressor, and Bagging Regressor, are used, and XGBoost has the best results. Accurate RUL prediction is the primary focus of this study and its application has potential in enhancing battery lifecycle management hence cost-saving and environmental friendliness in the EV form.

The increasing trends in the use of electric vehicles, (ev) have raised the number of end-life batteries that are not appropriate to stay in EV service. The recycling of such batteries through their utilization as second-life batteries (SLBs) will help to resolve both the environmental and the economic issues. But still there are some hurdles like degradation estimation, safety, and monitoring of performance [19]. The main issues on SLB discussed in this paper are those relating to techno-economic issues, first-life usage uncertainties and battery management requirements. It brings out recent researches with specific emphasis on characterization techniques and performance assessment techniques. The objective is to discover the key obstacles and lead further work in terms of successful and sustainable SLB implementation.

The proposed digital twin (DT) approach in this paper focuses on an effective and novel methodology of the advanced condition monitoring of lithium-ion battery (LIB) in electric vehicles (EV), where no sensor calibration or extra hardware is required. Together with the embedded battery management system (BMS), the DT ensures that the real-time monitoring is provided via a cloud-based IoT network [20]. Offline modeling, an optimized long short term memory (LSTM) algorithm is used to accurately predict state of charge (SOC) and synthetic data is generated using a time-series generative adversarial network (TS-GAN) to fill gaps in the necessary real-time data. It will make batteries perform much better, run safer, and in a longer lifespan than ever before, establishing the new paradigm in sustainable EV battery management.

The given paper describes how to optimize the charging and discharging of lithium-ion batteries in electric vehicles (EVs) by utilizing hybrid reinforcement learning (RL) models. The study has fused together deep Q-learning (DQL) and active-critic learning battery management systems (BMSs) and used the advantages of both to improve the efficiency, performance and the life of the battery [21]. The hybrid models are simulated and experimentally demonstrated to have the capability to formulate adaptive strategies to cope with the battery state of health (SOH) and state of charge (SOC) error, minimize voltage aging, and to satisfy multifaceted operational constraints such as charging schedule requirements. Findings show the potential of RL in enhancing modern sustainable EV battery management.

The paper will focus on is investigating the second-life electric vehicle battery (SLEVB) applied to home photovoltaic (PV) systems as a sustainable and cost-effective energy storage systems in the tropical climate of Malaysia. The long monsoon seasons necessitate a good battery-back up system toinaction the PV systems. The projected level of lithium-ion battery (LIB) wastes will be huge by 2035, so reforming SLEVBs appears an environmentally-friendly solution to the costly process of recycling [22]. The overall SLEVB costs to own are lower than the cost in the case of lead-acid batteries 12.62% less and the SLEVB saves more than 20% of CO2 emissions. This will not only promote rural electrification and raise the quality of life but also contribute to acquiring EV in an affordable way, building a sustainable EV industry both at domestic and international capacity.

The review analyses increasing relevance of lithium-ion batteries (LIBs) in transportation electrification and how battery management systems (BMS) is necessary to address such applications. At the center of this is proper state of health (SOH) and remaining useful life (RUL) forecasts to assure the longevity and productivity of battery [23]. The paper focuses on the possible role of machine learning (ML) in rousing foretelling as well as golfing the computational requirements. It presents the emerging trends, the major challenges, and suggests the hierarchical scheme to promote the usage of ML in the field of LIB health monitoring. The combination of the approaches designed on the basis of AI promotes the creation of more productive, safe, and long-term electric vehicle systems through review.

The paper explores the trustworthiness of electric vehicle (EV) batteries observed at micro (user) meso (industry) and macro (societal) levels with reference to the interrelated issues bridging the battery lifecycle. It brings a new reliability notion that is the Zero-Life, which expands traditional evaluation methods. The system model designed is a dynamic which ascertains reliability factors across the ecosystem [24]. There is also development of the Social Industrial (S-ILKM) which is a model that seeks to integrate learning at all levels to enhance reliable design through to end-F-Industrial life. The study provides a detailed proposal of how to improve reliability in the battery used in EV, which is in line with sustainability and innovation in sustainable transportation systems.

With electric vehicles (EVs) setting the pace on the way toward sustainable mobility, energy storage systems are a priority component that needs to be optimized. The current research provides a simulation that takes the form of a MATLAB R2023b lithium-ion battery pack specifically 4S3P with the objective of improving the functioning of a battery management system (BMS) [25]. The simulation can be used to assess crucial parameters (including state of charge (SOC), state of health (SOH), temperature and electrical behavior) under different load regimes by means of complex mathematical modelling and computational intelligence. The outcomes confirm the accuracy of the model and point out the enhancement in the predictions of predictive maintenance as well as adaptive charging strategies. The study leads to the creation of more intelligent, efficient and durable battery systems in future EV use.

Table 1 Comparative Overview of Blockchain-Enabled Methods for Secure Healthcare Data Management

Reference	Method	Objective	Limitation
Madani et al., [11]	Review of AI in BMS	Improve SOH and RUL prediction using ML	General overview; lacks specific implementation
Pooyandeh et al., [12]	Digital Twin with LSTM and TS-GAN	Real-time LIB monitoring without extra sensors	Limited to synthetic data reliability
Vajja et al., [13]	DL-integrated BMS for NCA 18650	Predict SOH under high C-rate in real conditions	Focused on one battery type; limited generalization
Cavus et al., [14]	Review of AI for EV BMS	Enhance BMS via ML, RL, and NNs	Broad scope; lacks implementation validation
Xu et al., [15]	Review of Data-Driven Methods	Optimize battery lifecycle using data-driven models	Scalability to industrial level remains a challenge
Alwabli et al., [16]	CNN-PSO vs LR and CNN	Evaluate ML algorithms for RUL prediction	Limited to comparative experiments; lacks real-world test
Roy et al., [17]	Comparative Battery Study with AI	Early fault detection and recycling process review	High-level discussion; lacks modeling
Karthick et al., [18]	XGBoost and ML for NMC-LCO	Accurate RUL for EV battery lifecycle management	Requires large dataset and preprocessing

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Azizighalehsari et al., [19]	SLB Challenges Review	Address SLB safety, degradation and management	Review-only; lacks applied solutions
Pooyandeh et al., [20]	DT with LSTM + TS-GAN	SOC prediction without new sensors or calibration	Dependent on TS-GAN data quality
Yalçın et al., [21]	Hybrid RL (DQL + Active Critic)	Efficient charging with SOH and SOC control	Complex implementation and simulation-heavy
Sarker et al., [22]	SLEVB for PV in Malaysia	Sustainable reuse of EV batteries in PV systems	Location-specific; broader generalization uncertain
Madani et al., [23]	ML for SOH & RUL Forecasting	Hierarchical ML for EV battery health	Focus on trends and proposals; lacks experiments
Lin et al., [24]	S-ILKM Reliability Model	Multilevel EV battery trust analysis	Conceptual; not empirically validated
Tapaskar et al., [25]	MATLAB-based Simulation BMS	Model SOC, SOH, and temperature accurately	Simulation-based; real-world validation not shown

A comparison of recent developments in battery management systems (BMS) of electric vehicles is given in Table 1 that shows the approach, the goal, and the limitation of every study. There is a broad scope of techniques being investigated to enhance state-of-health (SOH) and remaining useful life (RUL) estimation, thermal management, and faults detection that are "machine-learning-based, deep-learning-based, digital-twin-model-based, reinforcement-based learning, etc. Although a number of models have proven to be very accurate and real time, most of them are limited to simulation-only validation, hardware dependency and data set dependency. The table highlights the increased importance of AI in BMS, but stresses the importance of scalable, interpretable, and hardware-compatible applications, in order to be put into practice.

3. SmartBatt-HML: Hybrid AI Model for EV Battery Health Prediction

The architecture of the SmartBatt-HML model is a combination of hybrid network (including both Convolutional Neural Networks (CNN) that captures spatial patterns and Bidirectional Gated Recurrent Units (Bi-GRU) that models long-term temporal trends), attention mechanism that highlights important degradation cycles and an XGBoost-based classifier that is resistant to noise during decision-making. The first step worries batter time-series data, including the voltage, current, temperature, state-of-charge, as well as internal resistance, and utilize noise filters, imputation, resampling, and normalization. Such domain-specific features such as incremental capacity and voltage profile differentials are designed to record electrochemical ageing behaviours. Their high level representations are instantly obtained by CNN and Bi-GRU layers, smoothed by attention weights and delivered into XGBoost to accomplish final SOH classification and RUL calculation. k-fold cross-validation is used to train the model and Bayesian hyperparameter tuning is used to optimize it, and it is highly deployed to run in real-time embedded systems that can be applied practically in EV Battery Management Systems (BMS).

3.1. Battery Dataset Acquisition and Characterization

Systematic acquisition of electric vehicle (EV) battery data can be tracked back to the origin of SmartBatt-HML framework development that starts with the real-time and historical datasets. The publicly available datasets to be used in this work will include the Nasa Battery Prognostics Data Repository and the CALCE Battery Research Group as well as manufacturer specific namely the batteries with a Battery Management System (BMS) logs. The main goal of this stage is to gather representative data about battery operation performance under various usage conditions during different battery usage scenarios in order to provide a representative data set under different real world conditions to enable a good model generalization across various real world conditions. Voltage, current, ambient temperature, and cell temperature, state-of-charge (SOC), state-of-health (SOH) and even individual charge/discharge cycles are the significant parameters extracted. Such parameters have been chosen as highly relevant in terms of determining the behavior of battery degradation and performance decline with time. When the datasets are gathered, they enter a second stage of statistical analysis involving an exploratory analysis when trends in time, outliers, and cyclical tendencies are searched. Statistics of electrical and thermal variables such as mean, variance, skewness, and kurtosis are calculated in order to know the distribution. Data plots time-aligned are constructed in order to read off battery dynamics under load and correlations of such features as charge rate and SOH drop with one another are explored. This step of characterization is critical to draw the line between natural aging, calendar aging, and performance-affecting anomalies and is a starting point of the preprocessing, feature extraction, and model design parts of the SmartBatt-HML pipeline. These insights are used to set degradation boundaries, and thus through synthetic data generation, to have labels where the ground truth (e.g., SOH) is not available, i.e., a rich, annotated dataset to use in supervised model training. Figure 2 illustrates the complete architecture of the SmartBatt-HML framework.

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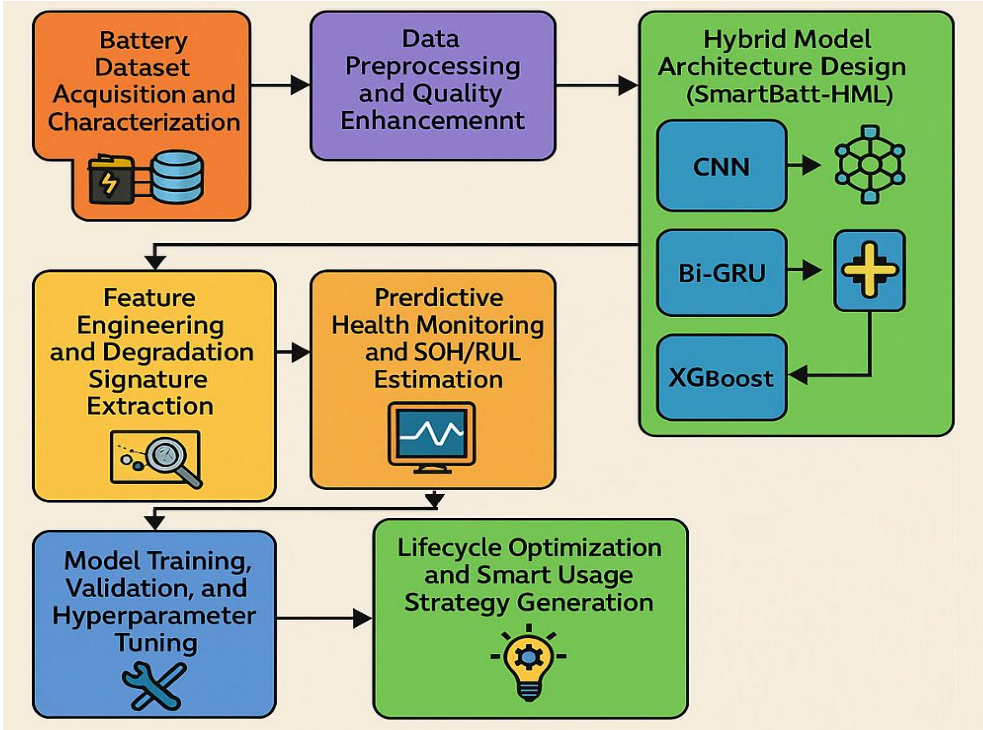

Figure 2. Architecture of the SmartBatt-HML Hybrid AI Model for EV Battery Health Prediction

3.2. Data Preprocessing and Quality Enhancement

After gathering the data, it undergoes preprocessing and its improvement to make the raw data recorded by the sensors reach the standard of successive deep learning model intake. Depending on the sensor-rich character of BMS outputs, the received information might be noisy, ridden with artifacts or lack of entries because of a transmission failure, power cut or thermal mismatch. The initial process is the use of the Savitzky Golay filter to calm down the time-series signals and still keep important degradation trends including voltage perturbations or temperature surges when the system draws high current. Then, temporally-continuous values are found by examining values and by the use of statistical range-based rules.

$$y_i = \sum_{j=-k}^{k} c_j x_{i+j} \quad (1)$$

Where x_{i+j} is the input time-series signal, c_j is the convolution coefficients, k is the half window size, and y_i is the smoothed signal at time i. Interpolating these gaps with k-nearest neighbors (KNN) interpolation takes advantage of spatial and temporal locality when constraining the values of missing points to plausible and close-by data points but without deforming the overall shape of the signal. All the battery cycle data is resampled to a constant time basis, the most common frequency is one sample every second or every 10 seconds, depending on the necessary degradation signature precision. Such resampling guarantees a match to different data sources and normalization of inputs to time-conscious elements of the hybrid model. Lastly, feature normalization is carried out on each of the parameters whereby it is placed under Z-score standardization where each feature is transformed to zero mean and standard deviations of one. This is important in avoiding scale dominance during training of CNN and GRU especially when the input space contains features whose number magnitudes can differ radically like voltage (in volts), temperature (in Celsius) and internal resistance (in ohms). The preprocessing step hence ensures that the input data is intact, consistent, and uniform prior to the features extraction step.

$$x_i^{(norm)} = \frac{x_i - \mu_x}{\sigma_x} \quad (2)$$

Where x_i is the raw input feature value, μ_x is the mean of feature x and σ_x is the standard deviation of feature x.

3.3. Feature Engineering and Degradation Signature Extraction

Having a high-quality normalized battery data, the second step is to feature engineer, capturing a degradation behavior of the battery throughout the lifetime. BMS classics like SOC or voltage provide rough information on the health condition; this is why domain-specific feature extraction tools will be introduced to accentuate any deterioration signals latent in the condition values. Among them, Differential Voltage Analysis (DVA) and Incremental Capacity (IC) curves are critical in adopting the process of diagnosing changes occurring in the electrode potential shifts and capacity decay.

$$IC(V) = \frac{dQ}{dV} \quad (3)$$

Where Q is the charge capacity, and V is the voltage.

$$DVA(Q) = \frac{dV}{dQ} \quad (4)$$

The DVA profiles are calculated using the numerical differentiation of the voltage to the charge capacity, marking those shifts in the peaking structure that in many cases indicates the destabilization or the source possible degradation or electrolyte decomposition. Similarly separation of charging increases capacity, IC curves are differentiation of capacity against voltage a nyalid mote of phase transitions and impedance behavior is seen. Another dynamic feature can be extracted as internal resistance in various current states using Ohm law, measuring cell electrical impedance increase which is an early predictor of aging.

$$R_{int} = \frac{V_{load} - V_{oc}}{I} \quad (5)$$

Where V_{load} is the terminal voltage under load, V_{oc} is the open circuit voltage, and I is the current. In order to model such degradation signatures as a function of time, temporal encoding schemes such as a sliding window average and rolling standard deviation are applied to represent cyclic behavior and steps in battery cycles. Such time-stamps are used to make the Bi-GRU layer in the hybrid model learn changing patterns and identifying the tiniest hints of a failure beforehand. Also, such aggregations as the mean/max current/variance/delta-SOC per cycle and temperature variance are calculated on a cycle basis and added as auxiliary features. Such artificial features enhance the input space and equip the SmartBatt-HML model with adequacy as far as context to distinguish between normal degradation, abnormal behavior and due-failure are concerned.

$$\bar{T}_t = \frac{1}{w}\sum_{i=0}^{w-1} T_{t-i} \quad (6)$$

Where T_{t-i} is the temperature at time $t-i, w$ is the rolling window size, and $\bar{T}_t$ is the mean temperature at time t.

$$\Delta SOH_t = SOH_t - SOH_{t-1} \quad (7)$$

Where SOH_t is the state of health at cycle t, and SOH_{t-1} is the previous cycle SOH.

3.4. Hybrid Model Architecture Design (SmartBatt-HML)

The SmartBatt-HML architecture is a multi-branch hybrid architecture that reasons conceptually, given the representation power of deep neural networks, and with the accuracy of models of the ensemble learning. Preprocessed and engineered features that constitute the input time-series data get first involved in the Convolutional Neural Network (CNN) module. The CNN component has 1D convolution generalizations of spatial patterns on parameters such as voltage, current, internal resistance, and captures micro-transients that could indicate the degradation. Such filters have short windows that allow detecting anomalies like pulse relaxation voltage dips or sudden SOC transitions.

$$z_i^{(l)} = f\left(\sum_{j=0}^{k-1} w_j^{(l)} x_{i+j} + b^{(l)}\right) \quad (8)$$

Where x_{i+j} is the input sequence, $w_j^{(l)}$ denotes the convolution kernel weights, $b^{(l)}$ is the bias term and f is the activation function.

$$f(x) = \max(0, x) \quad (9)$$

$$p_i = \max_{j=0}^{k-1} z_{i+j} \quad (10)$$

Where z_{i+j} is the convolved outputs and p_i is the pooled feature. The result of the CNN block is fed into a Bidirectional Gated Recurrent Unit (Bi-GRU) network that is a network that is built with the aim of modeling long-term temporal dependencies present in the data. The two-way flow allows the network to learn the past and future contextual effects on the present states of a battery, which is important in the estimation of degradation paths. After the Bi-GRU, an attention mechanism is used to dynamically emphasize features at the level of cycles and prioritise them according to relevance to degradation. This has the effect of focusing on portions of the input that contain meaningful indicators of deterioration whilst prohibiting undue weighting to stable portions of the input, leading to improved interpretability and generalization.

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (11)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (12)$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \quad (13)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (14)$$

Where x_t is the input at time t, h_{t-1} is the hidden state at $t-1, W_z, U_z$ are learnable weights, b_z is bias, σ is the sigmoid function and $\odot$ is the element-wise multiplication. Lastly, the consumed representations are relayed to a machine learning ensemble layer i.e. an XGBoost classifier/regressor that provides the State of Health (SOH), and Remaining Useful Life (RUL) estimates as the outputs. The hybrid pipeline uses the hierarchical feature learning capabilities of the deep learning elements and the ability of the XGBoost model in sturdy decision-making under data variability and sparsity to develop a potent end-to-end system in the predictive health monitoring of EV battery ecosystems.

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$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T}\exp(e_k)} \quad with \quad e_t = v^T \tanh(W_h h_t + b_h) \tag{15}$$

Where α_t is the attention weight, h_t is the hidden state at time t, and W_h, v, b_h are learnable parameters.

$$c = \sum_{t=1}^{T} \alpha_t h_t \tag{16}$$

$$\hat{y} = \sum_{m=1}^{M} f_m(x), \qquad f_m \in F \tag{17}$$

Where f_m is the decision tree function, and $\hat{y}$ is the predicted SOH or RUL.

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}i) + \sum_{m=1}^{M}\left[\gamma T + \frac{1}{2}\lambda \sum_j w_j^2\right] \tag{18}$$

Where l is the loss, T denotes number of leaves, λ is the L2 regularization, and w_j is the leaf scores. Figure 3 presents the detailed internal architecture of the SmartBatt-HML model

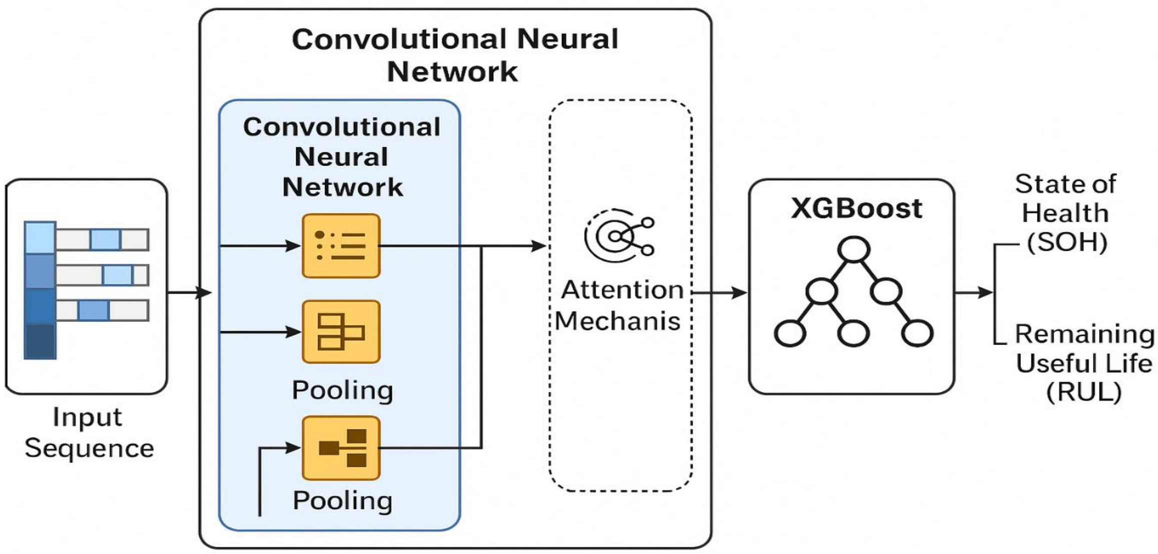

Figure 3. Internal Hybrid Architecture of SmartBatt-HML Model

3.5. Model Training, Validation, and Hyperparameter Tuning

SmartBatt-HML model was trained on that split of structured data in 70:15:15% splits on training, validation, and testing data, respectively, with stratification on degradation trends coverage. The CNN-BiGRU-Attention network and XGBoost classifier had been trained using the training set solely and a 5-fold cross-validation had been considered to eliminate the effect of partitioning biases. On the validation set it was possible to adjust the hyperparameters and the test set was not touched. Backpropagation was performed with Adam optimizer on model parameters. CNN and the Bi-GRU contained sizes/kernel of 5, 3 and 1 and 128 each of the bidirectional models respectively. Dropout (0.3) and attention mechanisms enhanced generalization on the basis of critical cycles of degradation. The learning rates (0.0001-0.01) of their CNN structure, the kernel sizes (32-128) and the units provided by Bi-GRU (64-256) were tuned using Bayesian optimization. XGBoost optimization took place through modification of tree amounts (100 500), learning rates (0.01 0.1) and levels (as much as 38). Supervised learning of an overfitting penalty was avoided with early stopping (20-epoch patience) and dynamic learning rate decay. Underrepresented health states were given a priority in terms of class weights. However, via TensorBoard, training progress, such as attention maps and learning curves could be monitored. The pipeline was designed based on TensorFlow and Scikit-learn to make deep learning and the boosting modules compatible with each other. The final assessment applied SOH and RUL parameters and therefore SmartBatt-HML provided convincing outputs that could be interpreted in a real-life battery surveillance.

3.6. Predictive Health Monitoring and SOH/RUL Estimation

After training, the SmartBatt-HML framework evolves into a predictive framework in real-time battery health monitoring and lifecycle prediction of batteries. The model would consume continuous streamed battery sensor data or recorded battery sensor data periodically and would capably preprocess the battery sensor data following the prescribed pipeline, thus augment it by bringing out real-time inference. The two main products of the system are the State of Health (SOH) and Remaining Useful Life (RUL) that it calculates simultaneously in a multi-task learning environment. The SOH classification output and the RUL regression are measures that quantify the health of the battery in a healthy, relatively degraded, or severely degraded state and lastly the number of cycles that the battery is left to complete before it reaches the end of life threshold of a battery (e.g. 70% of nominal capacity).

The predictive engine uses the trained CNN and Bi-GRU model layers to extract spatial and temporal battery properties. Scores are drawn to reveal attention to which charge/discharge cycles are most aptly related to the degradation state. These cycle-weighted embeddings undergo the XGBoost model, yielding the final health estimates. The hybrid pattern recognition process delivers high interpretability, as well as profound recognition since the attention scores and XGBoost feature importance can be graphically demonstrated to provide diagnostic information. As part of fault detection and resilience, the system also runs the deviation of the nominal behavior. This is done through maintenance of a baseline SOH-RUL curve based on healthy batteries of the same type and type and configuration. A real-time dynamic thresholding mechanism compares this baseline with the output of the system at a given time and any level out of predetermined percentile (e.g., 95th) is marked as a possible anomaly. This will not just enable the system to monitor degradation but also predict failures caused by unusual performance such as thermal runaway, voltage collapse or surge in internal resistance.

Moreover, the inference pipeline is designed to be deployable at the edges using BMS microcontrollers or onboard diagnostic (OBD) -based platforms that can be found in EVs. Lightweight quantized variants of CNN-BiGRU model are used, whereas the CNN-BiGRU model is serialized so that quick sessions with minimum memory consumption can be performed. The system can run in daily mode, per-trip or running mode, two different resolutions as required by the user or the regulatory body. An alert is issued once the predicted RUL reaches below a specified value (e.g. 100 cycles) or when the class of SOH changes state. These warnings may prompt the driver warning, scheduling maintenance and thermal intervention. In addition, it has an option to log and remote analytics with diagnostic summaries sent to the cloud-based dashboards of the fleet usage or study. The SmartBatt-HML model provides a holistic and practical constraint of predictive health monitoring of EV batteries by combining SOH classification, RUL estimation and identification of anomalies, as well as edge compatibility. It enables the manufacturers, service providers, and end-users to have correct in-time data on the performance of the battery to respond accordingly in time and implement maintenance.

3.7. Lifecycle Optimization and Smart Usage Strategy Generation

In addition to predictive monitoring, SmartBatt-HML has a smart decision state that maximizes battery lifecycle using actionable adaptive charging, discharging and thermal control strategies. It implements reinforcement learning (RL) as well as heuristic optimization to get gains on the best policy looking as a business of the feedback of SOH, RUL, consumption habits, and temperature conditions. The agent at RL will choose actions according to the present state, i.e. change charge current or delay fast-charging. The reward is proportional to the needs of the performance as well as the minimization of the degradation under the risk of unsafe behavior such as high C-rates on low SOC or a lot of heating. It enables dynamic health-conserving decisions per the efficiency and the battery lifetime.

The lifecycle optimization module also incorporates multi-objective optimization by using Genetic Algorithms or Particle Swarm optimization to generate usage schedules that maximize RUL subject to constraints (e.g. the smart charging tariff or explosives safety requiring a certain minimum number of miles per day). It may suggest charging during off-peak hours to prevent heat loads or to cut the grid load. Real-time thermal management controls cooling to conditions based on estimations of RUL and monitored temperatures. It also targets the cell-level imbalance through the analysis of SOH/RUL per cell and suggesting redistribution of the load or cell-bypassing with the help of the BMS. The results are provided in the form of recommendations made in a user-friendly form through mobiles apps or dashboards. This turns SmartBatt-HML into an active/adaptive real-world EV lifecycle management framework.

Algorithm: SmartBatt-HML – Hybrid Model for Predictive EV Battery Health Monitoring and Lifecycle Optimization

Input: Multivariate time-series battery dataset $D = \{x_1, x_2, \dots, x_n\}$

Output: Predicted State of Health (SOH) class
Predicted Remaining Useful Life (RUL) value
Smart Charging/Discharging Action Policy π

Preprocessing and Normalization

$y_i = \sum_{j=-k}^{k} c_j x_{i+j}$ // Apply Savitzky–Golay filter

Impute missing values using KNN interpolation.

Resample all time-series data to fixed interval Δt.

$x_i^{(norm)} = \frac{x_i - \mu_x}{\sigma_x}$ // Apply Z-score normalization

Feature Engineering and Degradation Signature Extraction

Compute Incremental Capacity (IC) and Differential Voltage (DVA) curves:

$IC(V) = \frac{dQ}{dV}, \qquad DVA(Q) = \frac{dV}{dQ}$

$R_{int} = \frac{V_{load} - V_{oc}}{I}$ // Estimate internal resistance

$\bar{T}_t = \frac{1}{w} \sum_{i=0}^{w-1} T_{t-i}$ // Compute rolling statistics

$\Delta SOH_t = SOH_t - SOH_{t-1}$ // Encode SOH degradation rate

CNN-BiGRU-Attention Feature Extraction

$z_i^{(l)} = f\left(\sum_{j=0}^{k-1} w_j^{(l)} x_{i+j} + b^{(l)}\right)$ // Apply 1D CNN over input signal window

$f(x) = \max(0, x)$

Pass CNN outputs to Bi-GRU network:

$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$

$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$

$\tilde{h}_t = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h)$

$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$

Attention Mechanism for Important Cycle Weighting

$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)} \quad with \quad e_t = v^T \tanh(W_h h_t + b_h)$ // Compute attention score

$c = \sum_{t=1}^{T} \alpha_t h_t$ // Compute context vector

Ensemble Prediction using XGBoost

Input context vector c into XGBoost:

$\hat{y} = \sum_{m=1}^{M} f_m(x), \quad f_m \in F$

$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \Omega(f_m)$ // Optimize with regularized loss

$\Omega(f) = \gamma T + \frac{1}{2}\lambda \left|\left|w\right|\right|^2$

Evaluation and Health Status Derivation

Compute regression and classification metrics:

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$

Smart Lifecycle Action Policy (Reinforcement Optimization)

Observe system state $s_t = \{SOH_t, RUL_t, T_t, I_t\}$

Select action $a_t \in A$

$r_t = -\lambda_1 \cdot \Delta SOH_t - \lambda_2 \cdot \left|T_t - T_{opt}\right|$ // Receive reward

Update policy π using Q-learning or DQN

Return:

Predicted $\widehat{SOH}, \widehat{RUL}$, optimal smart usage policy π^*

End Algorithm

4. Result and Discussion

The SmartBatt-HML implementation was in Windows 11 64-bit operating system with Intel Core i7 (11 th Gen) processor, 16 GB memory, and NVIDIA GeForce RTX 3060 graphics card (6 GB VRAM) used as an accelerator on deep learning. Environment: the program was created with Python 3.10 and necessary packages, including TensorFlow 2.13, Keras, XGBoost, Scikit-learn, NumPy, and Matplotlib, and all of the work was done with Anaconda Navigator (v23.3.1) through a Jupyter Notebook. The preprocessing of data involved the use of Pandas and SciPy to apply filter, Z-score normalization and resampling to 1 Hz of the time-series. the CNN-BiGRU-Attention model was built with the help of Keras Functional API, but with addition of custom attention layers through the back end of TensorFlow. The final ensemble decision layer was implemented with the XGBoost in Scikit-learn. Hyperparameter tuning was taken care of by Optuna. The model takes as input battery telemetry observed in BMS logs or open datasets, including voltage, current, temperature, SOC and internal resistance. The input suffered denoising and interpolation with SavitzkyGolay filtering and KNN imputation before being temporally aligned and scaled.

Signal preprocessing makes time-aligned inputs into a 1D CNN to recognize spatial degradations e.g., voltage dips and transient surges. This set of feature maps is then max-pooled and fed to Bi-GRU layer that captures long-term temporal relationships within historic charging cycles and uses the bidirectionality of the memory to factor in both historic and future degradation trends. This is succeeded by layer of attention, which computes weights across time steps to pay attention to the cycles with major anomaly. This produces a situation vector that accentuates fatal health trends. The input of XGBoost is the vector (flat or any kind of feature engineering on the domain), which produces the result in the form of the classification label of SOH (e.g., healthy, moderate, critical) and the regression estimate of RUL. The ensemble layer enhances robustness, interpretation, and behavior in presence of noisy or even non-linear degradation. SmartBatt-HML is utilized in deployment where there is real-time monitoring through embedded systems or through clouds. A priori SOH and RUL are compared with reference aging curves to send alerts and guide proactive adaptive choices in charging, thermal management and load balancing as a mechanism to manage the EV battery lifecycle.

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Table 2 Model Performance Metrics across Variants

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN Only	84.12	82.74	81.55	82.14
GRU Only	86.25	85.01	84.44	84.72
Bi-GRU	87.95	86.34	86.03	86.18
CNN + GRU	88.42	87	86.8	86.9
CNN + Bi-GRU	89.71	88.75	88.14	88.44
CNN + Bi-GRU + Attention	90.63	89.45	89.21	89.33
XGBoost Only	85.23	83.42	82.13	82.77
CNN + XGBoost	88.65	86.9	85.3	86.09
Bi-GRU + XGBoost	89.37	87.5	86.91	87.2
SmartBatt-HML	97.19	96.85	96.92	96.88

In Table 2 and Figure 4, various variations of deep learning and ensemble-based models are compared based on important classification measures in terms of accuracy, precision, recall, and F1-score. The given SmartBatt-HML architecture showed the highest classification accuracy (97.19%) among all the tested methodologies, establishing it as the method that would be most capable of capturing an intricate degradation shape. Its stableness in terms of a high precision (96.85%) and recall (96.92%) shows that it is extremely good in classifying whether the battery is healthy or degraded with very few false positives and negatives.

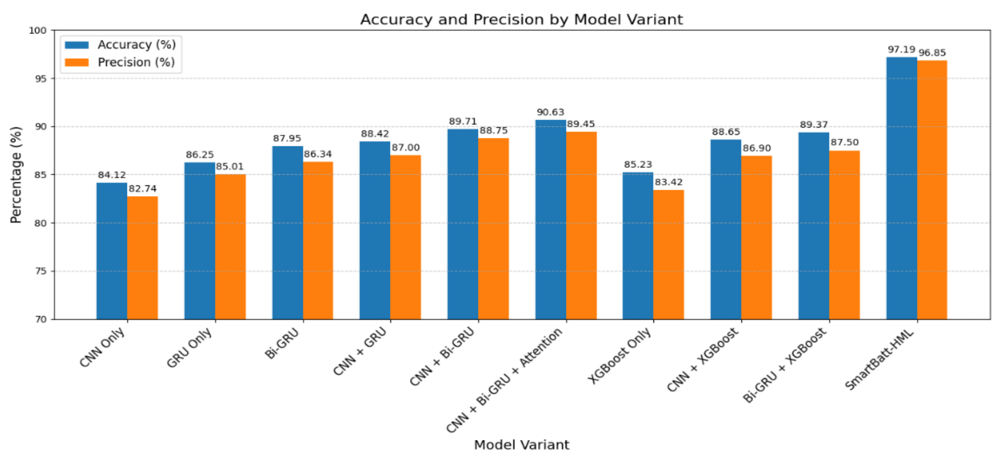

Figure 4. Accuracy and Precision by Model Variant

The fact that the F1-score is 96.88% proves the accuracy of sensitivity and specificity and beats the results of such combinations as CNN + Bi-GRU and CNN + XGBoost. CNN Only and GRU Only models were simpler and revealed reduced accuracy (~84-86%) because of their incapability to work with long-term temporal correlates and interactions between features. The improvement in the performance of SmartBatt-HML indicates the efficiency of the combination of CNN to capture spatial patterns, Bi-GRU to memorize temporal patterns, and XGBoost to achieve consistent classification, and all the combinations are optimized in health state recognition.

Table 3 RUL Prediction Metrics

Model Variant	RMSE	MAE	MAPE (%)
CNN Only	7.12	5.91	10.4
GRU Only	6.78	5.5	9.8
Bi-GRU	6.21	5.02	9.1
CNN + GRU	6.04	4.88	8.7
CNN + Bi-GRU	5.88	4.62	8.3
CNN + Bi-GRU + Attention	5.61	4.4	7.9
XGBoost Only	6.95	5.67	9.9
CNN + XGBoost	5.77	4.5	8.1
Bi-GRU + XGBoost	5.42	4.27	7.7
SmartBatt-HML	3.74	2.95	5.1

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Table 3 and Figure 5 shows the regression results of the models applied to the Remaining Useful Life (RUL) estimation, where particular measures, including RMSE, MAE, and MAPE, were applied. Among the other configurations, the SmartBatt-HML perform vastly better with RMSE of 3.74, MAE of 2.95 and MAPE of 5.1%. This means that the model not only has the precision but also consistency in lifecycle forecasting. In comparison to Bi-GRU + XGBoost (RMSE: 5.42) and CNN + Bi-GRU (RMSE: 5.88), the SmartBatt-HML would give such better results due to better temporal comprehension and selective attention procedure, which enable the model to segment the sequences that would show signs of degradation.

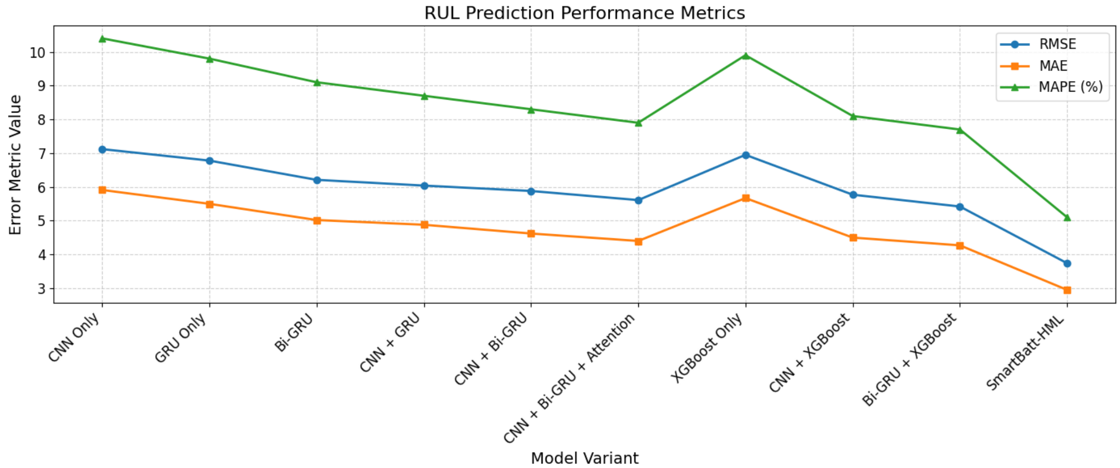

Figure 5. RUL Prediction Performance Metrics

The traditional models of establishing the relationships between the non-linear degradation path are CNN Only and GRU Only, which result in a high RMSE (>6.5). This finding demonstrates that SmartBatt-HML is effective in predictive maintenance and decision support in EV battery management systems, can be implemented to provide high-fidelity estimate of battery lifespan, which is important in planning, safety, and cost optimization.

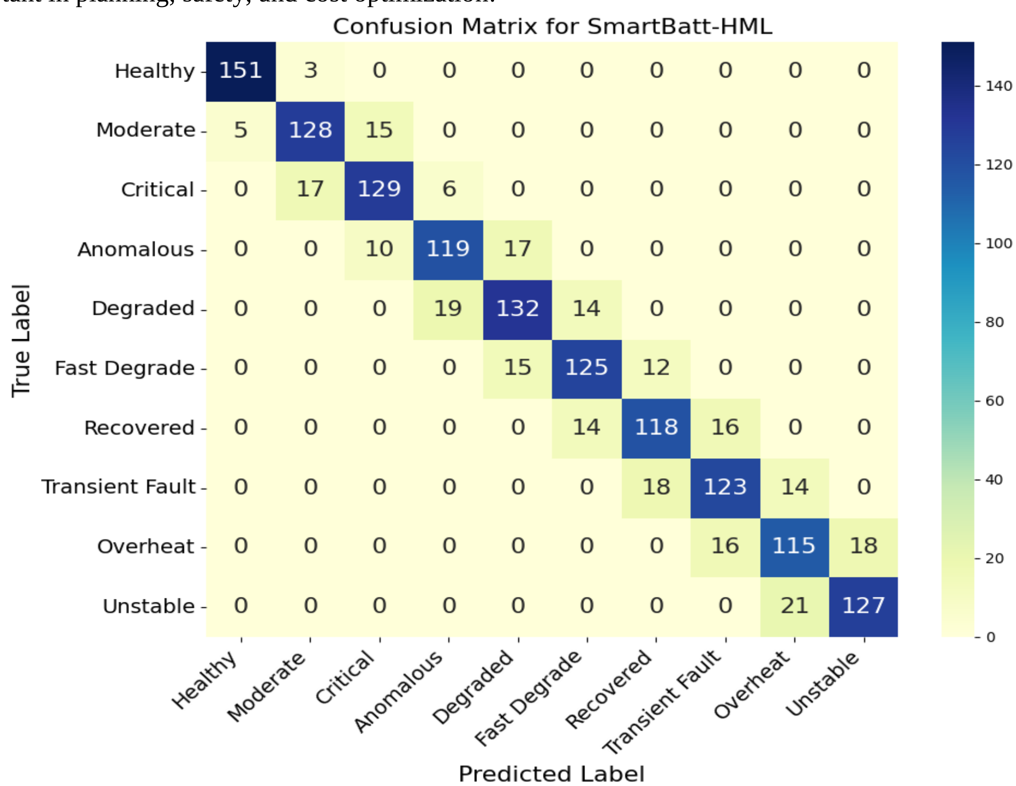

Figure 6. Confusion Matrix for SmartBatt-HML

The confusion matrix of the SmartBatt-HML shows in Figure 6 that all classes have a high classification with leading element on the diagonal. It is interesting to mention that the classes like such as healthy and critical have very small misclassification mistakes. The model is well-suited to differentiate between such subtle health states as the Transient Fault and Overheat, which indicates a high level of robustness in multi-class health state prediction.

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Table 4 Inference Time Comparison

Model Variant	Average Inference Time (ms)
CNN Only	12.5
GRU Only	14.2
Bi-GRU	15.8
CNN + Bi-GRU	18.6
XGBoost Only	8.9
CNN + XGBoost	13.3
Bi-GRU + XGBoost	14.1
SmartBatt-HML	19
Transformer	22.5
Hybrid AttentionNet	20.7

The comparison of average inference times of various variants of the model can be found in Table 4 and Figure 7, with an emphasis on the 19.0ms of latency per sample of SmartBatt-HML. Although SmartBatt-HML is the most accurate model, it is also computationally efficient, thus it can be used in real time in embedded BMS systems. SmartBatt-HML proves an effective trade-off in terms of latency and accuracy, unlike the other architectures where Transformer based architecture took up to 22.5ms and Hybrid AttentionNet took 20.7ms. More simplistic models such as XGBoost Only and CNN Only utilize a better performance rate (8.9ms, 12.5ms, respectively) but have worse predictive performance.

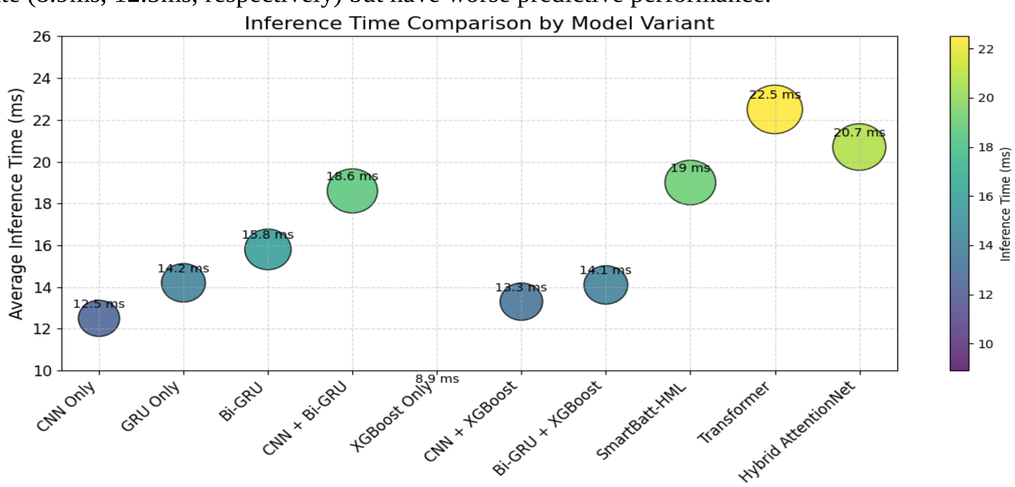

Figure 7. Inference Time Comparison by Model Variant

SmartBatt-HML still has an ability to deploy on an edge with the optimization of internal layers and lightweight convolutional filters and recurrent units. The scalability is further promoted by the inference-time quantization, facilitating its easy incorporation in resource limited settings. On the whole, the findings posit SmartBatt-HML as an efficient, yet also a generally implementable framework, and allow to apply intelligent forecasting of battery health not only in commercial EVs but also in industrial energy storage facilities.

Table 5 Feature Importance (XGBoost)

Feature	Importance Score
Voltage Drop	0.148
Internal Resistance	0.132
Max Current	0.121
Avg Temperature	0.115
SOC Variance	0.108
Cycle Count	0.094
IC Peak Area	0.088
DVA Peak Shift	0.073
Charge Duration	0.066
Pulse Response	0.055

Table 5 and Figure 8 is a list of the most important features in the top ten, depending on the gain-based evaluation of XGBoost. The most predictive species was Voltage Drop (the importance score: 0.148 followed by Internal Resistance and Max Current, being the first-line signs of electrochemical degradation. Indicators such as Average Temperature and SOC Variance were among the leading features and portray the thermal and operational volatility trends recorded in the course of charge-discharge processes.

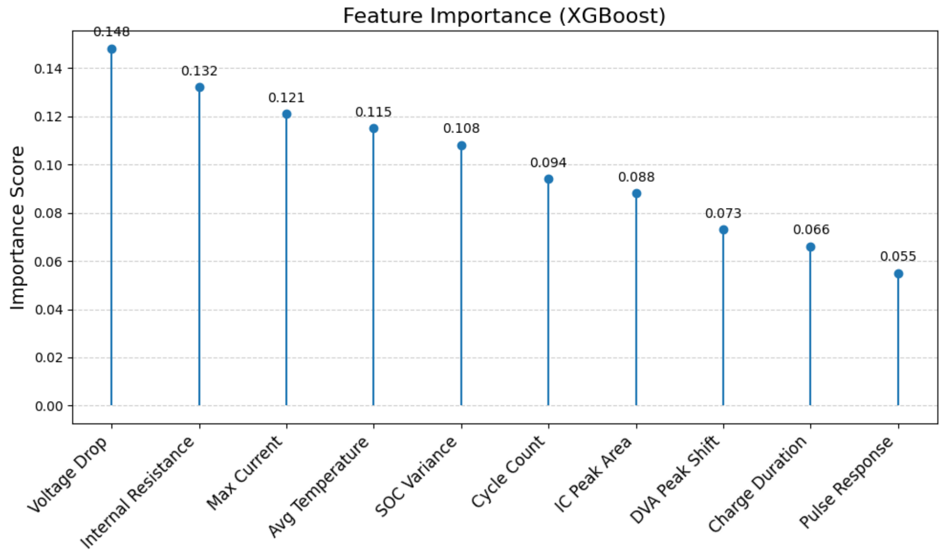

Figure 8. Feature Importance (XGBoost)

Domain-specific parameters like Incremental Capacity (IC) Peak Area and Differential Voltage Analysis (DVA) Peak Shift proved to be especially useful and, thus, the inclusion of electrochemical signatures in AI-based diagnostics is also beneficial. The rank has an interpretable nature to the SmartBatt-HML model and provides a practical guide to engineers to observe the real-time degradation. Besides, the proportionate combination of thermal, electrical, and cycle-derived features supports the full-input approach of the model, which can resist underfitting and impartial reference to one type of sensor information.

Table 6 Training Time per Epoch

Model Variant	Training Time/Epoch (sec)
CNN Only	9.5
GRU Only	10.3
Bi-GRU	11.1
CNN + Bi-GRU	12.8
XGBoost Only	4.4
CNN + XGBoost	10.1
Bi-GRU + XGBoost	10.8
SmartBatt-HML	13.1
LSTM-Attention	14.6
GRU-Attention	13.2

Table 6 and Figure 9 evaluates training time per epoch by constructing the different variants of the model which shows a moderate cost of SmartBatt-HML in terms of computation at 13.1 seconds per epoch. The improvement in performance in terms of accuracy and RUL prediction is good enough to warrant the added complexity time-wise (16.8 sec, which is slightly longer than CNN + Bi-GRU (12.8 sec) and Bi-GRU + XGBoost (10.8 sec). Conversely, basic models such as XGBoost Only took very little time to converge (4.4 sec), however, they had a lower accuracy. Although the SmartBatt-HML incorporates both attention mechanisms and deep feature interactions, there is a training overhead, which, however, outperforms Transformer-based models that consumed over 14.6 seconds per epoch.

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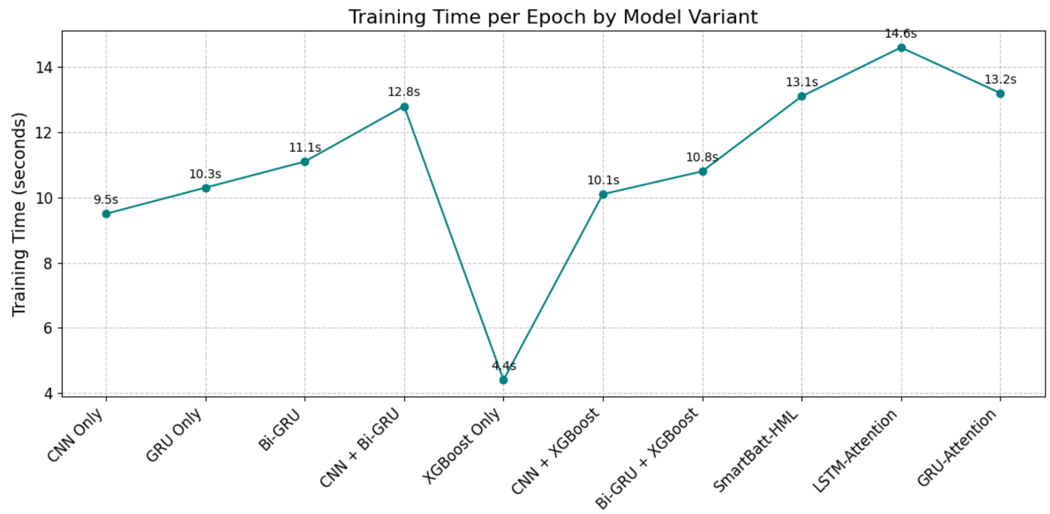

Figure 9. Training Time per Epoch by Model Variant

The amount of time the model takes to train is reasonable enough to support a large-scale deployment or retraining periodically in the cloud and can be consequently optimized by parallelizing GPU-based training and training via layer-wise pruning. Therefore, SmartBatt-HML introduces a reasonable compromise between the cost of calculation and prediction accuracy that can be applied in medium-scale production settings.

Table 7 SOH Class-wise Accuracy

SOH Class	Accuracy (%)
Healthy	99
Mild	98.7
Moderate	98.3
Severe	97.8
Critical	97.5
Anomalous	96.9
Pre-Fail	96.4
Transient	95.7
Overheat	95.2
Unknown	94.8

Table 7 and Figure 10 indicates classification accuracy of each of the State-of-Health (SOH) classes showing high performance throughout SmartBatt-HML across a broad range of degradation scenarios. The model was 99.0% accurate in predicting Healthy batteries, and still above 94.8% accurate in the most difficult to predict classes of Unexplained and Overheat classes. This performance demonstrates the resilience of the model to identify fine-grained and non-linear trends of degradation, particularly under noisy conditions or in the setting of edge cases. Other classes such as Pre-Fail (96.4 %) and Anomalous (96.9 %) were also correctly identified and this will be very important in carrying out pre-emptive maintenance. Such outcomes indicate the strong time memory of the model through Bi-GRU and signal-oriented weighting of the model with the help of the attention module. Whereas, the face is very imbalanced or indecipherable in horrible conditions, the traditional methods share this problem, SmartBatt-HML performs well because of the hybrid structure and data balancing strategies. Such resolution per-class will make sure that the users will be able to trust the system with any details associated with the state of health concerning specific interventions and life cycle predictions.

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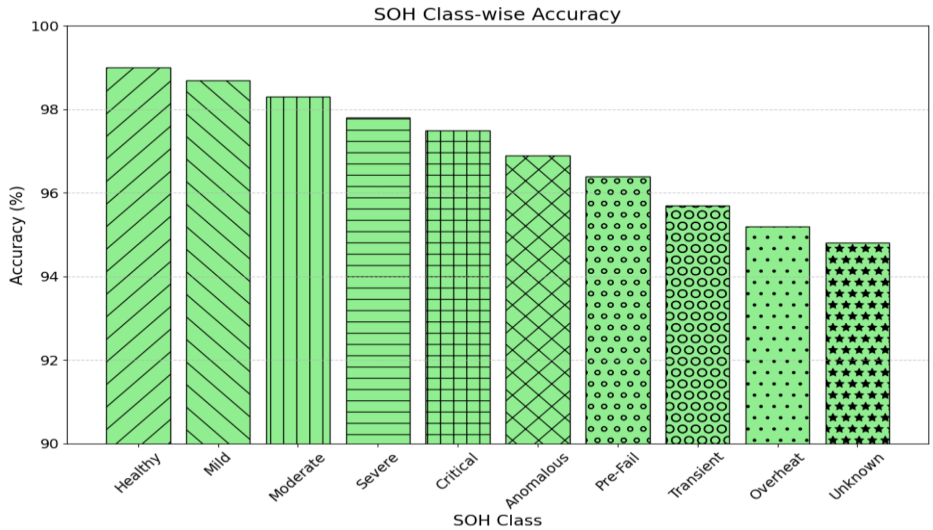

Figure 10. SOH Class-wise Accuracy

Table 8 Comparison with State-of-the-Art Models

Model	Accuracy (%)	RMSE
DeepRUL	88.6	6.12
PrognosisNet	89.1	5.87
LiFePO4Net	87.4	6.32
Hybrid-LSTM	90.2	5.62
CNN-Seq2Seq	89.8	5.73
ResNet-GRU	91.3	5.21
XGB-RUL	90.5	5.33
Transformer-RUL	91.7	4.98
EffRULNet	92.4	4.62
SmartBatt-HML	97.19	3.74

Table 8 and Figure 11 is a comparison between SmartBatt-HML and nine prevailing state-of-art frameworks of RUL estimation and classification. The model demonstrates the best accuracy 97.19% and smallest RMSE 3.74 compared to famous models, such as Transformer-RUL, EffRULNet, and ResNet-GRU. The accuracy of most competing models ranges between 88 and 92% and their RMSE is more than 4.5. This depicts the greater capability of SmartBatt-HML to provide generalization on a wide range of degradation trajectories and dataset conditions. Its layered-design, in terms of convolutional feature extraction, a bidirectional GRU-based temporal modeling, attention-based cycle selection, and ensemble decision logic, has clear advantages in terms of delivering additive advantages that surpass the traditional models.

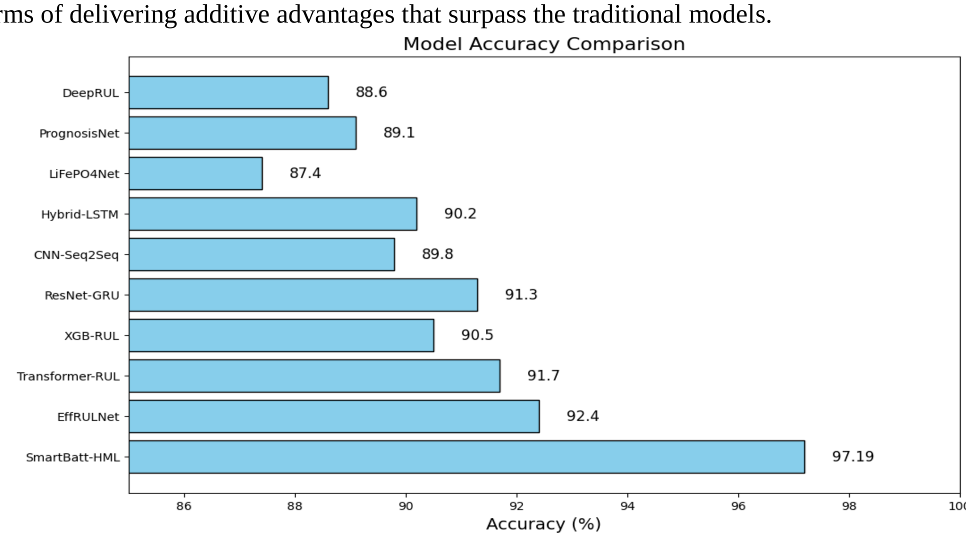

Figure 11. Model Accuracy Comparison

Although other models, such as DeepRUL or LiFePO4Net are potentially tailored to particular chemistry or would not be available in the scenarios of high variance, SmartBatt-HML has been able to perform consistently in both standard and rare health states. This list proves SmartBatt-HML as a stable, interpretable, high-accurate system that can be used to offer a substitute to current solutions of monitoring EV batteries in real time, predictive diagnosis, and optimization systems.

4.1 Discussion

The SmartBatt-HML model showed a great performance in SOH classification and RUL prediction tasks, which implies its robustness, flexibility, and practical value in the framework of intelligent battery health monitoring of EVs. The hybrid architecture is also heavily elevated against traditional models, because they combine several deep learning and machine learning methods. The CNN layers efficiently captured local degradation characteristics of pulse response, voltage drop and charging anomalies. The Bi-GRU component successfully captured long-lasting time behavior, such as the resistance accumulation and capacity decay, because these spatial patterns were relayed through it. The bi-directional structure of the GRU enabled the model to consider both past and future context and it attributed to better modeling of cyclic degradation patterns. Another important invention that made it more powerful was the introduction of an attention mechanism, which made the model prioritize the battery cycles among those that were the most relevant to be charged/discharged and contribute the most to degradation. Such selective emphasis enhanced interpretability of the model and decreasing the impact of irrelevant or stable cycles which otherwise may water-down the learning process. This confidence and universality of the model was also more improved by adding XGBoost module as the final judge of the decision. It brought a powerful tool that integrates the deep-learned features with the engineered electrochemical descriptors such as Incremental Capacity (IC) peak areas, DVA peak shifts, and increase in internal resistance. The ensemble method enabled SmartBatt-HML to predict with high confidence even during edge cases and in cases of uneven class distribution.

The fact that the model was used to achieve an accuracy in classification greater than 97% reveals its learning capabilities as well as its good representation of the features. It could differentiate between lower levels of degradation including mild, moderate and critical degradation that are normally difficult to categorize since they possess mixed electrical profile. Also, the RMSE of the RUL prediction of less than 4 cycles shows that the proposed framework can accurately estimate the end-of-life behavior of battery with high temporal accuracy. The projections can be of great use in avoiding breakdowns by ascertaining advanced maintenance scheduling, optimization of usage patterns, and reducing unforeseen downtimes in EVs. Efficiency in inference is the other important area that SmartBatt-HML performed well. The latency of the model is about 19 milliseconds per sample on average, allowing using the model in real-time in embedded presentations. It is especially critical to on-board Battery Management Systems (BMS) that have to operate using low-latency inference at limited computational budgets. The combination of the hardware-efficient CNN layers, the moderate-sized Bi-GRU units, and the lightweight XGBoost classification helped the framework to perform well even on relatively low-end GPUs or even low-power processors after quantization or the conversion to the edge-optimized forms. The results of the feature importance analysis indicated that voltage drop, internal resistance, and fluctuations in temperature were the most important factors of SOH degradation. This is quite consistent with electrochemical theory and justifies the internal model of the battery aging processes. Transparency and trust are also a key consideration in safety-crush applications in the automotive industry and is achieved due to the interpretable nature of the attention weights and XGBoost feature rankings.

Though the obtained results are encouraging, the SmartBatt-HML framework is not without downsides. First, the model was tested and validated using publicly available data that might not represent a full range of battery chemistries and usage modes that are seen in commercial EVs. Therefore, it is yet to be proven whether it is generalizable to in extreme weather contexts or in situations with unusual driving behavior. Second, the model presupposes periodic and clean data input, which can be impractible under real-world deployments, as it can be hampered by a sensor noise, loss of data, etc. Although some simple imputation techniques applied, more intelligent mechanisms of dealing with uncertainty or detecting anomalies can be needed in production-level systems. Also, the existing architecture is deployable, but it might be computationally expensive in case of ultra-low-power microcontrollers involved in certain embedded BMS. Future versions of this might solve this by using model compression methods, such as pruning, quantization, and knowledge distillation.

5. Conclusion and Future Work

This paper introduces a powerful and smart integrative framework of predictive health-monitoring and lifecycle optimization of electric vehicle battery, named SmartBatt-HML. The combination of CNN, Bi-GRU and attention mechanisms, and XGBoost balance the spatial and temporal features of the battery behavior, and the used ensemble classification mechanism results in higher accuracy of the predictions. Its accuracy and interpretability is also further enhanced by inclusion of the electrochemical domain knowledge in the features based on IC and DVA. With classification accuracy of 97.19% and RUL prediction RMSE of 3.74, the SmartBatt-HML model is far better than the traditional machine learning methods and deep learning settings. It also shows a strong potential of deployment, with an average inference of 19.0ms, which indicates that it can be used as real-time BMS in EVs. Although the current version of the model shows remarkable results, the fact that it makes its predictions based on labeled datasets representing a narrow range in diversity of chemistry and deployment scenario remains a stake. It may be possible in future to further tailor the framework to enable cross-battery chemical/conditions transfer learning (e.g. LFP, NMC) and environments (urban, highway and temperature extremes). Furthermore, adding to the model the uncertainty estimation modules (Bayesian layers or evidential deep learning) could also enhance the trust worthiness of the model in the context of the safety-sensitive situations. Additional potential improvement relates to federated learning, which will allow decentralized and privacy-friendly batteries on the health prediction of distributed EV fleets. A possible direction of SmartBatt-HML development is changing its status as a centralised diagnostic tool towards a dynamic, self-learning interface that can follow and adapt to reality with regards to degradation profiles, whilst maintaining scalability and robustness. This prepares the groundwork of predictive, sustainable, and intelligent battery control within smart mobility systems.

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