Advanced AI-driven battery state estimation using deep learning and ensemble models

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ABSTRACT

Accurate estimation of the state of charge (SOC) and state of health (SOH) of lithium-ion batteries is essential for improving the performance, safety, and lifespan of electric vehicles (EVs). Traditional estimation methods often face challenges such as high computational complexity, limited adaptability to battery aging, and reduced accuracy under varying operating conditions. To overcome these limitations, this paper presents a hybrid data-driven framework that combines machine learning and deep learning techniques for SOC and SOH prediction. For SOC estimation, linear regression, recurrent neural networks (RNN), gated recurrent unit (GRU), and stacked long short-term memory (LSTM) models are employed. For SOH prediction, ensemble learning methods, including stacking regressor, tree-based pipeline optimization tool (TPOT) regressor, and hybrid GRU-LSTM models, are utilized. The proposed models are evaluated using publicly available lithium-ion battery datasets under different charge–discharge conditions. Results show that deep learning approaches achieve superior performance, with GRU-LSTM and stacked LSTM models providing highly accurate SOC estimation ($R^2 \approx 0.993$, RMSE ≈ 0.015), while the TPOT-based ensemble model delivers near-perfect SOH prediction ($R^2 \approx 1.0$). A web-based implementation further enables real-time battery monitoring, demonstrating the framework's practicality for advanced battery management systems (BMS) in EV applications.

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1. INTRODUCTION

Historical statistics reveal that the vehicular transport's contribution to carbon-related emissions has been climbing progressively to roughly thirty-seven per cent after transport-related limitations related to the COVID pandemic got relaxed [1]. The transport industry is more reliant on energy from petroleum than anything else, and transportation on roads accounts for the majority of the emissions of greenhouse gases [2]. To address such climatic impacts, international growth-centric strategies need to change their focus to a carbon-free society [3]. The advancement of battery-wide tech is fundamental to this change, serving as a vital facilitator of a future that is more environmentally friendly [4]. With this focus change inclined towards a more sustainable resource and electric mobility, both the dependability and efficacy of battery packs have become critical [4], [5]. Lithium-ion composition-based battery packs hold the wide range of potential of serving the electric-operated vehicles and renewable source power-based facilities across the nation [6]-[8]. Such kinds of battery packs require periodical, accurate monitoring of the critical parameters in order to prevent it from unforeseen unnecessary performance-centric degradation, and to assure off safer operation all the time.

The global transition towards electric mobility and sustainable energy systems has led to widespread adoption of lithium-ion battery packs across electric vehicles (EVs). and grid-connected storage facilities [9], [10]. These battery packs serve as the backbone of modern energy applications, necessitating accurate and real-time monitoring to ensure safety, efficiency, and longevity [11]-[13]. Among the core parameters used in battery diagnostics are state of charge (SOC), which reflects the available charge, and state of health (SOH), which indicates the aging and usable lifespan of the battery [14]. However, estimating these metrics accurately is an ongoing challenge due to the complex, dynamic nature of battery behavior under varying operational and environmental conditions [15].

In recent years, the growing embracement of portable electronic circuitries, sustainable EVs, and renewable resource-powered systems has significantly increased the requirement for dependable battery-pack management facilities [16], [17]. Among the core parameters that define battery performance, both the measures like SOC and SOH take up a vital part [18]. Accurate estimation of these metrics is needed for enhancing the lifespan of battery pack, assuring off the improved protection, and optimizing energy usage [19]. Traditional estimation techniques often fall short due to their reliance on physical models, sensitivity to environmental conditions, and inability to generalize across battery types and usage patterns [20], [21]. The advent of deep learning, with its potential to compile sophisticated non-linear associations from raw info, offers a promising alternative. We develop an intelligent, real-time, and a much adaptable solution for battery state computation that takes advantage the prospects of hybrid deep learning models. By combining algorithms such as linear regression, recurrent neural network (RNN), stacked long short-term memory (LSTM), and tree-based pipeline optimization tool (TPOT) regressor, we aim to sort out the constraints of conventional approaches and improve predictive accuracy. The ultimate goal is to contribute toward safer and more efficient battery usage in critical applications, thereby advancing the progression of intelligent, sustainable energy administration facilities.

When it comes to the battery-centric monitoring, two of the metrics play a key role, which are as follows: SOC and SOH [22]. The level of the current charge corresponding to the full capacity of a battery pack is denoted by SOC [23]. Likewise, the aging and remaining usable life with regard to the battery pack are denoted by SOH [24]. If the estimation of SOC is made inaccurately, then it can cause unexpected shutdowns. Similarly, if the SOH has been misjudged, then it can cause early battery replacements or failures. The existing methods available for such estimations frequently depend upon certain physical models and manual calibration, lacking the adaptable capability against the variable operational conditions.

Numerous methodologies have been proposed to address SOC and SOH estimation, a few have been discussed below. Fankhauser *et al*. [3] clarified the concept of “net zero” emissions, emphasizing that it is not just a numerical target but a strategic framework requiring deep, real emissions cuts alongside carbon removal. The authors caution against over-reliance on offsets and urge policymakers to ensure credibility, transparency, and equity in net-zero commitments. They advocate for sector-specific pathways, robust accounting mechanisms, and coordinated governance to align climate action with scientific goals. Their work stresses the importance of transforming the plans into actionable progress, which helps to provide the clarity on definitions, timelines, and responsibilities. The contribution made by the authors helps to promote the decarbonization, offering a comprehensive understanding of climate policy design.

Gandoman *et al.* [25] undertake an exploration of fundamentals and advancements concerning the assessment of reliability and safety of lithium-ion battery packs in EVs. Their exploration covers the critical failure modes, diagnostics, and test methods that aids the evaluation of battery health and prevention of accidents. They successfully reviewed the modelling techniques, aging mechanisms, and thermal-centric issues with emphasis on the lack of standardization and the requirement of real-time data integration. Their work highlights the significance of multidisciplinary techniques that used a combination of electrical, thermal, and mechanical models for obtaining accurate assessments.

Liu *et al*. [26] made use of a simplified pseudo-two-dimensional (P2D) electrochemical model to present a dual estimation method for SOC and SOH of a battery pack. This work demonstrates the benefits that the integration between the electrochemical modelling and estimation algorithms yield by providing highly accurate insights on the internal dynamics of a battery pack from time to time. As the work can account for battery degradation effects (like lithium plating and capacity fade), it can empower the real-time health monitoring of a battery pack. The developed model holds the potential to balance between complexity and computational efficiency, which makes it ideal to manage the battery packs in any electrical facility. The authors in this work have contributed much towards the enhancement of predictive maintenance and reliability of lithium-ion battery packs installed within EVs and grid storage.

Liu *et al*. [27] perform a discussion on the critical technologies that shape the battery management systems (BMS) in electric vehicles. The main emphasis of the work was on certain core functions like cell balancing, thermal management, charge control, and fault detection. This work identifies the important role played by critical factors like accurate SOC and SOH estimation, communication protocols, and integration with vehicle control platforms. The authors discuss the schematic of both the hardware and software components with attention given to emerging trends like cloud-based monitoring and AI-driven analytics. This review investigation made by them stresses the existing constraints like cost reduction, data security, and the integration of advanced sensors. The contribution made by the work offers sound technical knowledge that the future researchers and engineers can leverage to design robust BMS platforms.

An extensive overview of thermal management strategies was presented by Ding *et al.* [28] to sort out the technical constraints realized in battery packs of EVs. The authors categorize methods into air cooling, liquid cooling, phase change materials, and thermoelectric technologies, analyzing their effectiveness, cost, and feasibility. The paper also explores novel techniques like nanofluids and hybrid systems that combine passive and active cooling. It emphasizes the significance of thermal uniformity in enhancing battery performance and lifespan. Additionally, it discusses control algorithms and design optimization techniques for efficient heat dissipation. This reference is crucial for ensuring battery safety, improving energy efficiency, and supporting the evolution of high-performance EV systems.

Shrivastava *et al.* [29] review state-of-charge estimation techniques for lithium-ion batteries, with a focus on the Kalman filter family (extended Kalman filter (EKF), unscented Kalman filter (UKF), and cubature Kalman filter (CKF)). It compares the strengths and limitations of each variant and discusses their applicability in real-time BMS. The study highlights how model-based estimation improves robustness under varying operating conditions and battery aging. The authors also examine implementation challenges, such as modelling accuracy, computational cost, and sensor noise. This paper is essential for understanding how advanced filtering techniques can enhance the reliability of battery charge estimation, especially in applications demanding precision, such as autonomous EVs and energy storage systems.

Li *et al.* [30] used multi-source data depending upon a unique deep transfer learning technique to tackle the problem of health-conscious battery designing. To improve the battery design's training process, a deep transfer learning technique was created that allows state estimators to be established using operating data from various EV kinds. Data on battery functioning gathered from two different kinds of electric buses was used to validate the approach. The battery model error may be kept to 2.43% and 1.27% throughout the life cycle with the help of the transfer learning technique and the established healthy state perception design.

A data-driven approach based on sparse Gaussian process regression (GPR) and the random partial charging process was developed by [31]. Initially, the partial charging process's random capacity increment sequences (Q) at various voltage segments were taken out. Q's average value and standard deviation were employed as characteristics to show the condition of the battery. High correlations between the characteristics and battery SOH were confirmed at various temperatures and discharging current rates after a correlation study was performed for three distinct battery types. The final step involved building sparse GPR models to estimate the SOH using the suggested characteristics as inputs.

Tian *et al*. [32] suggested a versatile approach that addresses the issues of condition of health and SOC estimates at the same time by estimating maximal and remaining capacities using just brief charging data. The suggested approach was based on a convolutional neural network (CNN) that can estimate two states using just short-term charging data. Eight 0.74 Ah batteries' deterioration data served as the first basis for validating the suggested approach. Subsequent tests on two more battery types demonstrated that the suggested approach may guarantee accurate estimate under various operating situations and battery chemistries. A versatile and simple mechanism for accurately estimating many states across battery life was provided by the method.

A study of battery state estimate techniques depending on several ML techniques and Hamming networks was presented by [33]. The approaches were compared based on declared accuracy, test settings, battery types, inputs and outputs, and data quality to provide readers with a broader perspective of the ML landscape for SOC and SOH calculation. When comparing estimate methodologies, it was suggested that the networks under comparison should be trained and evaluated using the same data and have a comparable number of learnable parameters.

Yang *et al.* [34] used the discharge curves to suggest a new health indicator. Investigations were conducted on how temperature, current, and depth-of-discharge affected the health indicator. The unique health indicator was then used to characterize the health condition of batteries that had aged at varying rates and depths of discharge. Batteries operating in various regimes have their SOH evaluated using an empirical model. The new health indicator proved successful and practical for satellite battery SOH estimate, according to the satisfactory estimation findings with a maximum error of 4%.

For estimating SOH, Wang *et al*. [35] alone took a new health indicator from the constant voltage profile's monitoring parameters. A novel indication was created after the equivalent circuit model was used to first define the battery aging processes during the constant voltage profile. It was suggested to use a framework for extracting this indication online. The performance evaluation and correlation analysis further demonstrate the flexibility and efficacy of the suggested approach for determining the health status of lithium-ion batteries.

A hierarchical estimating approach that takes the current rate into account was developed by [36]. Battery states were estimated using a multiscale dual extended Kalman filter (DEKF), parameters were identified using the data-driven technique, and the fractional-order model was employed for battery modeling. Comparing the suggested technique to classic DEKF under two situations, the accuracy of SOC estimate increased by 35.8% and 36.5%, respectively. Under two current circumstances, the accuracy of SOH estimate was increased by 34.8% and 43.1%, respectively, using the suggested technique.

Khan *et al.* [37] suggested MCCPs BMS to use the DL idea to estimate the health and capacity of batteries, where the patterns in these CPs alter as the battery matures over time and cycles. This led to a thorough investigation of both ML and DL-dependent approaches in order to offer a tangible comparison of the two approaches. Support vector regression (SVR) and adaptive boosting (AB) were extensively tested with CNN, multi-layer perceptrons (MLP), bi-directional LSTM (BiLSTM), and LSTM in order to determine the best method for estimating battery capacity SOH. BiLSTM surpasses all other techniques, as demonstrated empirically using the NASA battery dataset to confirm and verify the suggested strategy.

Hu *et al.* [38] created and experimentally verified a unique co-estimation hierarchy for lithium-ion battery SOC, SOH, and state of power (SOP). For accurate estimates and modest computing cost, a multi-time-scale estimating framework was designed taking into account the underlying connection and features among various states. A number of operational restrictions were respected by the model-dependent real-time SOP estimate, which accurately projected the battery peak power given updated states and parameters. Lastly, many tests were conducted to show the combination SOC/SOH/SOP estimation's durability and efficacy. When compared to independent estimation solutions, experimental findings demonstrate the significant advantages of the suggested co-estimation hierarchy. Both new and old cells had SOC, voltage, and capacity estimate errors of less than 3%, 25 mV, and 3%, respectively.

Traditional physics-based models, such as equivalent circuit models (ECMs) and electrochemical models, have been extensively used for SOC/SOH estimation, as reviewed in [26], [29]. While effective in controlled settings, these models often demand detailed battery characterization and are computationally expensive. Recent research has shifted towards data-driven methods:

- Liu *et al.* [26] proposed a joint SOC/SOH estimation technique leveraging a pseudo-2D electrochemical model, which enabled enhanced real-time monitoring by capturing internal dynamics.
- Tian *et al*. [32] introduced a CNN-based method for simultaneously predicting SOC and SOH from short-term charging data, offering a lightweight yet accurate framework.
- Xu *et al.* [36] employed a hierarchical multiscale Kalman filter-based approach that significantly improved SOC and SOH estimation accuracy under variable current rates.
- Khan *et al.* [37] evaluated traditional ML (e.g., SVR, AdaBoost) against deep learning techniques (e.g., LSTM, BiLSTM), revealing BiLSTM's superior performance for SOH prediction using NASA battery datasets.
- TPOT regressor, as explored in [33], utilizes automated machine learning (AutoML) for model selection and hyperparameter tuning, providing promising outcomes for SOH predictions without manual intervention.
- Kalman filter-based approaches like EKF and UKF [29] offer reliable performance under steady conditions but tend to falter when battery dynamics change due to aging, temperature variation, or irregular usage.
- Electrochemical models [26], while accurate, demand complex physical modeling and are not well-suited for real-time, scalable implementations.
- ML methods like SVR, AdaBoost, and XGBoost [37] handle nonlinear patterns but often depend heavily on manual feature engineering and hyperparameter tuning.
- CNN-based dual estimation [32] addresses both SOC and SOH, but may underperform when the charging data lacks variation or granularity.
- Liu *et al.* [26] and Shrivastava *et al*. [29] highlight the limitations of model-based approaches, establishing the motivation for data-driven solutions.
- Li *et al.* [30] and Tian *et al.* [32] demonstrate the growing success of deep learning in battery diagnostics, laying the foundation for using RNN and LSTM in our SOC modeling.
- Vidal *et al.* [33] conduct a survey comparing ML methods, justifying our decision to test multiple models side-by-side under the same dataset and conditions.

- Khan *et al.* [37] empirically prove that BiLSTM outperforms other models for SOH—this supports our rationale for using stacked LSTM for SOC due to similar temporal dependencies.
- Deng *et al.* [31] and Yang *et al,* discuss feature engineering from partial charge/discharge cycles, reinforcing the idea that effective models can be trained from common operational data.
- Xu *et al.* [36] introduce a hierarchical estimation model, which inspires our modular approach with decoupled pipelines for SOC and SOH.

These studies confirm the growing interest in machine learning and deep learning for battery diagnostics. However, most of them treat SOC and SOH as isolated problems or rely heavily on complex training setups, lacking real-time adaptability and unified system design. Also, reliable and highly computational SOC and SOH estimate algorithms are required, as well as the ability to modify in response to the practical-sense operating situations (temperature variations, age, and so on) with minimum information used for training.

Despite notable advancements, current methods for estimating SOC and SOH suffer from multiple limitations:

- Lack of real-time adaptability: Many methods fail under dynamic operational conditions due to their static modeling assumptions.
- Absence of unified systems: Few frameworks simultaneously address both SOC and SOH computation using distinct but integrated models.
- Manual model tuning: Conventional techniques often require domain-specific expertise for calibration, limiting scalability.
- Inadequate end-user integration: Most research implementations are not deployable through user-friendly interfaces, making them inaccessible to non-specialists.

These gaps highlight the need for a modular, intelligent system that can predict both SOC and SOH using hybrid, adaptable methodologies while being deployable in real-world settings. Accurate and real-time estimation of battery pack-centric measures-viz., SOC and SOH remains a substantial challenge in energy facilities, particularly in electric-operated vehicles and smart grids. Conventional estimation techniques, such as Kalman filters and electrochemical models, often suffer from high complexity, low adaptability, and sensitivity to environmental changes [39], [40]. These models may not generalize spanning upon the distinct battery pack variants, operational circumstances, and degradation patterns, leading to inaccurate predictions. Furthermore, unified models for both SOC and SOH are difficult to construct due to differing data characteristics and dependencies. This limitation poses risks such as inefficient battery utilization, reduced operational safety, and increased maintenance costs. As battery systems scale in size and importance, the need for a flexible, intelligent, and precise estimation method has become critical [15]. The problem is further compounded by the lack of accessible tools that integrate machine learning-based predictions into practical applications for end-users. The key issues include: i) non-linearity of battery behavior under diverse operating conditions; ii) variability in degradation rates due to temperature, usage patterns, and cell chemistry; iii) lack of universal modeling approaches—what works for SOC may not work for SOH; iv) need for real-time inference with high accuracy in safety-critical applications; and v) difficulty in collecting high-quality labeled datasets, especially for SOH.

Therefore, this work addresses the urgent need to develop a robust, real-time, and user-friendly dual-model framework using deep learning techniques to precisely compute both SOC and SOH, assuring better energy administration and battery longevity. In our work, we make use of data-centric and hybrid deep learning methodologies with the prime aim of addressing the aforesaid limitations experienced in the battery pack of EVs. We take advantage of historical and real-time data collected with wide range of sensors, which empowers the learning of complex battery behavior patterns to offer vigorous predictions of SOC and SOH. In our work, we make use of linear regression, RNN, stacked LSTM, gated recurrent unit (GRU), and GRU-LSTM for SOC, and Stacking and TPOT regressor, linear regression, GRU, and GRU-LSTM for SOH. The entire system constructed by us using the aforesaid methodologies has been implemented as a user-friendly web application. We have used multiple tools serving unique roles. We make use of Python to do the model development and integration. Also, we make use of other tools like HTML, CSS, and JavaScript for powering the interface to offer smoother user interaction. The developed hybrid framework can successfully offer a scalable solution, permitting the real-time battery state monitoring to serve various industries. This can eventually improve the energy efficiency and lifecycle management of power systems.

This work introduces a hybrid deep learning framework that addresses the above challenges by:

- Developing separate, optimized models for SOC and SOH prediction, tailored to the respective datasets (fetched from a single source) and behavioral dynamics.
- Employing a comparative methodology, wherein three techniques—linear regression, RNN, and stacked LSTM—are used for SOC computation, and two—stacking regressor and TPOT regressor—are used for SOH.

- Incorporating GRU and GRU-LSTM models to enhance SOC/SOH estimation through improved sequence learning capabilities. GRU offers a lightweight and efficient solution with fewer parameters, ideal for fast SOC estimation, while the GRU-LSTM hybrid model combines the memory retention strengths of LSTM with the computational efficiency of GRU to provide robust predictions for long-term degradation patterns.
- Integrating AutoML (TPOT) for automatic pipeline optimization, ensuring minimal human intervention for model tuning.
- Deploying a full-stack web application using Python (Flask) for backend modeling and HTML/CSS/JS for the frontend interface, thus enabling real-time, user-accessible predictions.
- Evaluating and benchmarking all techniques with industry-standard metrics (R^2, MAE, MSE, RMSE), validating the robustness and reliability of the models.

This dual-model approach allows users to input battery data and instantly receive SOC and SOH estimations, making it suitable for practical deployment in EVs, smart grids, and BMS platforms. The principal objective of our work is to build a strong, real-time, and accurate facility for the computation of both measures-viz., SOC and SOH of battery packs made of lithium-ion composition using hybrid machine learning models. Specifically in our work, we look to:

- Generate a separate deep learning methodology towards the computation of SOC using linear regression, RNN, and stacked LSTM, ensuring accurate prediction of battery charge level under varying operational conditions.
- Create an advanced ensemble-based model using stacking regressor and TPOT regressor for SOH estimation, focusing on capturing long-term battery degradation patterns.
- Integrate both models into a Python-based backend and connect them with a lightweight, responsive frontend interface using HTML, CSS, and JavaScript.
- Allow users to input battery parameters or sensor data through a web interface and receive practical-sense estimations of battery pack-centric measures-viz., SOC and SOH.
- Ensure that the facility is modular, interpretable, and capable of adapting to new data or battery types with minimal retraining.

By fulfilling these objectives, the work contributes to smarter battery management, improved safety, and longer battery lifespan—especially in grid storage facilities and electric-powered vehicles where battery performance is much-critical. The remaining sections of the manuscript have been organized as follows: i) Section 2 details the proposed methodology, including model architectures, operational flow, and algorithm selection. ii) Section 3 presents experimental results using visualization plots and a comparative table of evaluation metrics. iii) Section 4 concludes the study by highlighting the achieved results, practical relevance, and directions for future work—including real-time IoT integration and model generalization using transfer learning.

2. PROPOSED COMPUTATION METHODOLOGY

The decline in the capacity of battery packs and diminishing power is caused by a number of interrelated factors, rendering the investigation difficult and diverse. Across the age of the battery pack, its ability to operate diminishes, hence, correct SOC calculation requires a methodology that takes into consideration of deterioration of the battery pack. Similarly, an incorrect SOC estimate might cause mistakes in adjusting the SOH of a battery pack. As a result, contemporaneous calculation of SOC and SOH is widely acknowledged as critical for successful battery pack administration facilities. Despite the fact that deep learning methodologies have demonstrated favorable outcomes in the computation of SOC and are regularly cited in literature, these are typically researched separately, with no complete comparison study. This limits their comprehension of their particular abilities and constraints in particular use settings, when selecting the best strategy is critical for peak functional ability. The investigation provides an in-depth strategy, comparing 5 widely used methodologies across the identical settings. Out of the seven methodologies used, we use five methodologies for SOC computation, and we use five methodologies for SOH computation.

Consequently, we are introducing seven state-of-the-art methodologies with the two different aims as shown in Figure 1. Those two aims are the computation of both the battery pack-centric measures like SOC and SOH by segregating three methodologies for the former and two methodologies for the latter as denoted in Figure 1. As far as the data considered is concerned, we separate the data accordingly to compute battery pack-centric SOC using five methodologies- viz., linear regression, RNN, and stacked LSTM, GRU, and GRU-LSTM GRU, and GRU-LSTM, GRU, and GRU-LSTM and simultaneously, compute battery pack-centric SOH using five methodologies viz., stacking regressor, TPOT regressor, linear regression, GRU, and GRU-LSTM.

The notable contributions of our work are as follows:

- By integrating a range of models—linear regression for interpretability, RNN and stacked LSTM for temporal pattern learning, and AutoML tools like TPOT and stacking regressor for ensemble learning—we offer a diversified modeling approach.
- Importantly, we introduce GRU and GRU-LSTM models to enhance the framework's capacity for learning both short- and long-term dependencies in battery behavior. GRU provides lightweight, fast-converging predictions with fewer parameters, ideal for real-time SOC estimation. The GRU-LSTM hybrid combines the computational efficiency of GRU with the deep memory retention of LSTM, offering robust performance for both SOC and SOH tasks.
- Our architecture maintains a modular design that separates SOC and SOH pipelines while using a unified preprocessing and deployment structure—an approach rarely seen in prior works.

This comprehensive integration of traditional, ML, and advanced deep learning models enables greater flexibility, accuracy, and scalability for real-world battery diagnostics.

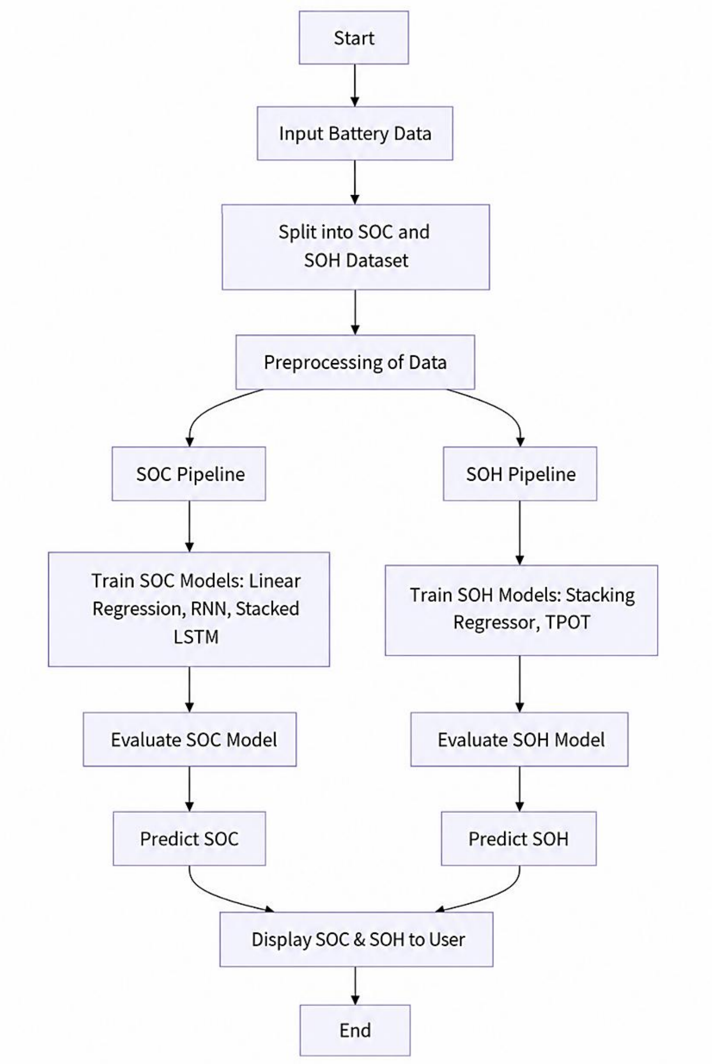

Figure 1. Block diagram of computing battery SOC and SOH with state-of-the-art methodologies

2.1. Objectives

In our work, we introduce a hybrid deep learning framework for the precise computation of measures like SOC and SOH in the battery packs made up of the lithium-ion composition. Unlike traditional model-based approaches, this system uses separate, specialized machine learning models trained on historical datasets (fetched from a single source [41]) to predict two measures like SOC and SOH. In case of SOC prediction, methodologies like linear regression, RNN, and stacked LSTM are implemented to capture both linear and temporal relationships in battery charge patterns. In case of SOH, which depends on degradation trends over time, ensemble-based methodologies such as stacking regressor and TPOT regressor are employed to ensure robust generalization. The entire backend is developed using Python, allowing integration of preprocessed datasets, model training, and real-time inference APIs. The frontend part has been compiled with the deployment of tools like JavaScript, CSS, and HTML, providing a clean user interface where users can input relevant sensor data or battery parameters. The system then returns real-time SOC and SOH values. This modular and dual-model design ensures scalability, interpretability, and adaptability to different battery chemistries and use-cases. Overall, it enhances BMS and energy storage reliability in EVs, drones, smart grids, and consumer electronics.

Estimating the SOC serves as the fundamental real-time indicator, enabling a safer and efficient battery operation throughout daily use cycles. The computation of SOC is critical for immediate operational decisions because it tells users how much energy remains available at any given moment. This prevents over-discharge, causing permanent damage to the cells of a battery pack. The innovative idea behind this work is to determine the battery pack's SoH using data acquired at the time of the course of charge operation. The ending of a charging procedure is a particularly critical time to obtain SoH data. With this information, consumers are able to figure out how the battery pack would get utilized. To accomplish so, we deploy two methodologies, which are taught and assessed using data collected while taking charge.

2.2. Outline of experimental/method section

This section outlines the complete experimental design, data sources, preprocessing steps, modeling techniques, performance evaluation strategies, and web-based implementation employed for the estimation of SOC and SOH in lithium-ion battery packs using hybrid machine learning and deep learning methods.

2.2.1. Dataset description

Two separate datasets were fetched from a single source [41] and subsequently used for SOC and SOH prediction tasks:

- The following are the key traits of the SOC dataset:
  i) Type: Publicly available EV battery cycling dataset.
  ii) Features: voltage (V), current (A), temperature (°C), time (s).
  iii) Target: SOC (%), updated per cycle.
- The following are the key traits of the SOH dataset:
  i) Type: NASA battery prognostics dataset.
  ii) Features: Cycle number, terminal voltage, charge capacity, temperature, and internal resistance.
  iii) Target: SOH (%), defined as the ratio of current capacity to rated capacity.

Note: Both datasets were cleaned and formatted into CSV files and were subsequently imported using Pandas (v1.5.3) in Python 3.10 for processing.

2.2.2. Data preprocessing

The preprocessing pipeline was implemented as follows:

- Data cleaning: First, we removed rows with missing or corrupted sensor readings. Then, we excluded outliers beyond 3 standard deviations using Z-score normalization. Finally, we filtered SOH dataset to retain full charge-discharge cycles only.
- Feature scaling: StandardScaler from Scikit-learn was used to normalize all continuous features (zero mean and unit variance) before feeding into the models.
- Train-test split: Each dataset was split into 80% training and 20% testing partitions using stratified sampling to maintain distribution consistency.

2.2.3. Experimental setup

- Hardware: Intel Core i7, 16GB RAM, 512GB SSD.
- Software: i) Python 3.10, ii) TensorFlow 2.11.0, iii) Scikit-learn 1.2.2, iv) TPOT 0.11, v) Flask 2.2.2, vi) Pandas, NumPy, Matplotlib, Seaborn.

2.3. Substantial contributions and novelty

This work introduces several novel contributions that set it apart from existing literature in the field of battery diagnostics.

2.3.1. Dual-model architecture

Unlike previous studies that either focus on State of Charge (SOC) or State of Health (SOH) independently, or attempt to use a single model for both, this work adopts a modular dual-pipeline architecture. SOC and SOH are estimated using distinct, specialized learning algorithms tailored to the respective characteristics of charge behavior and degradation patterns. This modular design enables each prediction task to be optimized independently, resulting in improved estimation accuracy, greater model flexibility, and enhanced adaptability to diverse battery operating conditions.

2.3.2. Methodological innovation

For SOC estimation, five comparative models are evaluated: linear regression (as a baseline), RNN, GRU, stacked LSTM, and a hybrid GRU-LSTM model. This expanded suite of models ensures the framework captures a wide range of temporal dependencies—from short bursts to long-range patterns. For SOH estimation, two ensemble-based approaches are implemented: stacking regressor and TPOT regressor. TPOT leverages AutoML via genetic programming to automatically construct and optimize pipelines. The combination of manually configured temporal models (e.g., GRU, LSTM) with AutoML pipelines (e.g., TPOT) in a unified framework for dual-state estimation represents a unique contribution not previously explored in related work.

2.3.3. Performance validation

All models were rigorously trained and tested under consistent conditions using publicly available real-world battery datasets, and evaluated using industry-standard metrics—R^2, MAE, MSE, and RMSE. The GRU and GRU-LSTM models achieved excellent accuracy for SOC estimation, with the GRU-LSTM model matching the top-performing stacked LSTM ($R^2 = 0.9935$, RMSE = 0.0147). The TPOT regressor achieved perfect prediction for SOH ($R^2 = 1.0$), establishing a new benchmark on the dataset.

2.3.4. Web-based deployment

This work includes a complete full-stack deployment, consisting of a backend powered by Python (Flask) and a frontend developed using HTML, CSS, and JavaScript. Users can interact with the system in real time to input battery data and receive instant SOC and SOH predictions, thereby bridging the gap between model development and practical utility. This deployment demonstrates the feasibility of integrating advanced battery estimation models into user-friendly applications, making the proposed framework suitable for real-time BMS applications in electric vehicles.

2.3.5. Future-ready design

The framework's modular structure facilitates seamless extensions, including IoT-enabled BMS integration, cloud-hosted analytics, and mobile deployment. Lightweight models, such as the GRU, ensure efficient implementation on edge devices while maintaining high prediction performance. Furthermore, scalable AutoML components prepare the system to accommodate future datasets and evolving battery diagnostic requirements, thereby enhancing its long-term adaptability and practical applicability.

2.4. Goals of the design and development approach

The design and development of the proposed framework were guided by the following core objectives:

- Accuracy: To ensure high predictive performance for both SOC and SOH across diverse battery conditions, leveraging robust modeling strategies such as GRU, GRU-LSTM, and stacked LSTM that can capture both short-term dynamics and long-term degradation trends.
- Adaptability: To build a flexible, model-agnostic architecture that supports quick adaptation to different battery chemistries, configurations, and operational environments—enabled by modular pipelines and transferable learning mechanisms.
- Scalability: To create an efficient yet extensible framework, where lightweight models like GRU can be deployed on edge devices for real-time SOC estimation, and more complex models like GRU-LSTM and TPOT can be scaled to centralized cloud systems or fleet-level battery monitoring.
- Usability: To develop a responsive and intuitive web interface that allows domain experts—engineers, researchers, or technicians—to input battery parameters and retrieve SOC/SOH predictions without needing ML expertise.
- Automation: To integrate AutoML via TPOT for dynamic model discovery and tuning, reducing manual configuration and enabling the system to continuously evolve and improve as more data becomes available.

2.5. Methodologies

Here, we briefly explain the seven methodologies used in our work concerned with computing both the battery pack's SOC and SOH. The following seven methodologies were used across the two target tasks, and their respective hyperparameters were either tuned manually or optimized using TPOT.

2.5.1. Linear regression

Linear regression is a foundational supervised learning methodology used to model the association between one or independent parameters and a continuous dependent variable. In simple linear regression, the relationship is represented by (1).

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{1}$$

Where x denotes the input feature (i.e., voltage, current), y denotes the forecasted resultant (i.e., SOC), β_0 is the intercept, β_1 is the slope (coefficient), and ε is the error term.

It is a key approach in the area of machine learning. Linear regression is a form of supervised learning in which the framework examines trained data with labels (such as data logs) to detect trends before using those trends to generate forecasts about fresh data. The word "linear" indicates the straight path structure of the modeled connection, whereas the word "regression" indicates the procedure of calculating the manner in which parameters return to their mean readings.

The model works by reducing the mean squared error (MSE) between the actually existing values and predicted values using methods such as ordinary least squares (OLS). For battery SOC estimation, this methodology presumes a linearly-existing association amongst sensor readings and charge level, which is valid in steady-state regions of the charge-discharge curve. Though simple and interpretable, linear regression cannot model non-linear or time-dependent battery behaviors. However, it's often used as a baseline or for systems where quick, real-time estimations are more important than ultra-high accuracy. It's fast, lightweight, and requires very little preprocessing, making it suitable for initial model deployment or integration into resource-constrained systems.

In simpler terms, it identifies trends in data by identifying links among parameters. As an illustration, a business that deals with real estate may utilize asset scale for prediction of house values, whereas a merchandiser may employ previous data on sales for prediction of earnings for the future. To make extremely reliable forecasts, the approach estimates simultaneously the intercept and the slope.

We apply linear regression for the SOC estimation by leveraging the relationships between measurable battery parameters and actual charge levels. This learning approach is being trained upon diverse range of historical data like voltage measurements, current patterns, temperature readings, and their corresponding known SOC values. With the identification of linear trends between the input parameters and charge state, the regression model can establish mathematical relationships for predicting SOC for subsequent new data.

We apply linear regression for the SOH estimation with the capture of gradual degradation patterns owing to batteries aging. The method can analyze long-term trends in performance indicators such as capacity fade, internal resistance changes, and voltage response characteristics. Then, it can correlate those indicators with known SOH benchmarks against the testing or specifications. With this SOH estimation, the overall health condition and remaining useful life can be forecasted.

The critical facts of linear regression are as follows: i) Tool: Scikit-learn's LinearRegression (), ii) equation: SOC = $\beta_0 + \beta_1 x + \varepsilon$, iii) purpose: Baseline comparison for SOC prediction using a linear model, iv) limitation: Inability to capture non-linearity in battery behavior.

2.5.2. RNN

RNNs are a type of neural system that is created exclusively to serve data that is sequential in nature. On the contrary to standard feedforward neural systems, this methodology features loops, allowing data to be saved. At each duration stage, an RNN acquires an input vector along with the hidden level from the preceded stage, producing a new hidden level and possibly an output. Mathematically, the relationship is expressed in (2).

$$h_{\mathrm{t}} = f(W_{\mathrm{x}} x_{\mathrm{t}} + W_{\mathrm{h}} h_{\mathrm{t-1}} + b) \tag{2}$$

This design enables RNNs to "remember" past information, making them ideal for modeling time-series data like battery sensor readings over time. However, benchmark RNNs experience diminishing or blowing up gradient problems, especially for long sequences, which hampers learning long-term dependencies. For battery SOC prediction, RNNs are powerful because they consider previous time steps while estimating the current charge level. For example, if a battery has been discharging steadily for the last few minutes, that trend is captured and used to refine the current SOC estimate.

In this work, RNN is used to model the temporal behavior of batteries during charging and discharging cycles. This inclusion can aid the capture of certain patterns like voltage drop rates or current variations corresponding to the SOC-centric changes. Despite the fact that RNNs can take more time to train and preprocess the data, it can still boost the prediction accuracy in dynamic environments owing to its potential to deal with sequential dependencies. The critical facts of RNN are as follows: i) Framework: Keras + TensorFlow backend, ii) architecture: Input layer → 64 RNN cells → Dense layer → Output, iii) activation: tanh (hidden), linear (output), iv) optimizer: Adam (lr = 0.001), v) loss: MSE, vi) epochs: 100; Batch size: 32.

2.5.3. Stacked LSTM

Stacked LSTM network is an enhanced version of a RNN that has been designed to consider the long-range temporal dependency across the time-series-typed data. On the contrary to a conventional RNN, this network consists of a memory cell along with three gates like input gate, forget gate, and output gate. The data passage is usually modulated by making use of such gates. This enhanced architecture can sort out the diminishing gradient issue, thereby this architecture can be much steady at the time of training with the deployment of long series.

It hosts several levels on it, wherein the levels are placed over one another. The outcome series produced by one of the LSTM levels will become input to the succeeding LSTM level and so on. Its in-depth architectural set-up makes it possible for the network to learn short-termed and long-termed patterns across the several extraction levels. Each layer of this network serves the purpose of capturing different features. The lower layer can capture the basic trends. Likewise, the high layer can capture complex interactions.

This network is able to effectively learn the dynamics of charging and discharging cycles from time to time for the sake of estimating the SOC. When the historical data like voltage, current, and temperature readings into the model are fed into the model, it predicts the current SOC with high precision irrespective of non-linear and fluctuating conditions. Though computationally intensive, stacked LSTMs offer superior accuracy in capturing complex battery behaviors, rendering this methodology to be appropriate for real-time uses, wherein precision is significant for the administration and protection of battery pack. The critical facts of stacked LSTM are as follows: i) Framework: Keras, ii) architecture: 3 LSTM layers (64, 32, 16 units respectively) → Dense layer → Output, iii) dropout: 0.2 (after each LSTM layer), iv) purpose: capture long-term temporal dependencies and improve generalization over charging cycles.

2.5.4. Stacking regressor

Stacking regressor is an ensemble learning approach that integrates forecasts from several kinds of foundational learning mediums for improvising the net operational functionality. In case of stacking, several regression methodologies (e.g., decision tree, SVR, ridge regression) are trained in parallel over the same dataset that was deployed earlier. Then, a meta-learning medium is trained on the outcomes of these base methodologies to make the final forecast.

This approach holds the potential of leveraging the strengths of diverse algorithms. For instance, while one model may perform well in linear regions of data, another may handle outliers or non-linear patterns better. By combining them, stacking reduces bias and variance, resulting in more generalized and accurate predictions. Mathematically, let $f_1(x)$, $f_2(x)$, ..., $f_n(x)$ be base models. The meta-learner g() learns from $[f_1(x), ..., f_n(x)]$ to predict the final output. It uses cross-validation to prevent overfitting during training.

For SOH estimation, this is extremely valuable. Battery health is influenced by many factors like temperature, usage cycles, and internal resistance. Stacking can integrate diverse insights from multiple models, capturing various facets of degradation.

In this work, stacking regressor is trained on SOH-related features to produce a robust estimate. It outperforms single models by adapting better to complex patterns in battery degradation behavior. The critical facts of stacking regressor are as follows: i) Tool: Scikit-learn StackingRegressor; ii) Base Learners: SVR, ridge regression, random forest; iii) Meta-Learner: linear regression; iv) Validation Strategy: 5-fold cross-validation.

2.5.5. TPOT regressor

TPOT regressor is a tool based on AutoML. It uses genetic programming to automatically explore and optimize machine learning pipelines, including data preprocessing, model selection, and hyperparameter tuning. TPOT searches through a wide range of models like gradient boosting, random forests, KNN, and their combinations to find the best-performing pipeline.

The working mechanism involves evolving a population of pipelines over several generations. Each pipeline is evaluated using a scoring function (e.g., R^2, MAE), and the best ones are selected to undergo crossover and mutation to generate new pipeline candidates. This mimics biological evolution to find an optimal solution over time.

In SOH estimation, TPOT is valuable because it automates the trial-and-error process of finding the best model and parameters. Considering the sophisticated nature and changeability of battery pack deterioration data, TPOT identifies the most effective model pipeline that can adapt to such diversity. In this work, TPOT regressor is used on the SOH dataset to identify a high-performing pipeline. It reduces human effort while ensuring strong model performance, making it ideal when working with datasets that have mixed feature types or unknown relationships.

The critical facts of TPOT regressor are as follows:
- Tool: TPOT (Tree-based Pipeline Optimization Tool) v0.11.
- Configuration: i) Generations: 5, Population Size: 20, and ii) Scoring: R^2, early stopping enabled.
- Outcome: Automatically generated pipeline involving Gradient Boosting + Preprocessing transformations (e.g., PCA, RobustScaler).

2.5.6. GRU

The GRU constitutes a form of RNN structure that is being predominantly used for diverse range of applications. A GRU, similar to various RNNs, is capable of analyzing sequential info including voice, natural language, and time sequence. The primary distinction amongst a GRU and different RNN designs, for instance, an LSTM network, lies in the manner in which the connection manages the movement of data as time goes on. It interprets series information like natural language or time series, while ignoring the hidden phase spanning between one period of time and the another. The phase that remains hidden is a form of vector containing data pertaining to the prior time leaps associated with the present time leap. The primary principle underlying this methodology is that it lets the system select which info from the previous time leap is important to the present one and which might get ignored.

Its topology has 2 gates, namely, i) update gate and ii) reset gate. Every gate has a distinct role, which greatly contributes to its outstanding effectiveness. The former recognises longer-duration links, whereas the latter detects shorter-duration links. The GRU is a strong answer to the issues of serial processing of information. It has evolved into an essential component in a variety of machine learning applications by solving the constraints of classic RNNs with new gated techniques. It had a significant influence upon diverse range of realms like time sequence forecasting, speech detection, and natural language processing, and it remains to motivate future advances in deep learning technology for series information.

The SOC estimation with GRU can intelligently process the temporal patterns in battery behavior through its dual-gate architecture. The update gate determines the retainability of the historical battery performance data with the estimation of current charge levels. The reset gate identifies the significance of short-term fluctuations in voltage, current, or temperature readings.

The SOH estimation with GRU method can address the battery degradation patterns across the extended periods through its intelligent gating mechanism. The update gate preserves critical long-duration degradation trends such as capacity fade rates along with internal resistance changes that could develop over hundreds of charge-discharge cycles. Similarly, the reset gate focuses on shorter-duration health indicators like sudden performance drops or recovery patterns that could correspond to specific degradation mechanisms.

The critical facts of GRU are as follows:
- Framework: Keras + TensorFlow backend
- Architecture: Input layer → GRU layer (64 units) → Dense layer → Output
- Activation: tanh (hidden), linear (output)
- Optimizer: Adam (learning rate = 0.001)
- Loss: mean squared error (MSE)
- Epochs: 100; Batch Size: 32
- Purpose: Efficiently capture short- and mid-range temporal dependencies in SOC data with fewer parameters than LSTM, making it suitable for lightweight or real-time applications
- Advantage: Faster training and inference with comparable accuracy to LSTM.

2.5.7. GRU-LSTM

The combination of GRU with LSTM, is commonly designated as an ensemble or hybrid framework, constitutes an effective way to use the capabilities offered by 2 topologies. Because of its combination construction, the framework could employ the capabilities of both GRU and LSTM techniques. It can successfully record longer-duration dependence, although GRUs can be technically superior and might work exceptionally well under some situations. By merging these two individual approaches, the resultant combination framework may work superiorly on a variety of activities.

The reason for adopting this hybrid GRU-LSTM framework is that each architecture has distinct strengths-GRUs is superior in processing the sequences quickly with the deployment of a fewer parameters due to their simplified gating mechanism and LSTMs can offer superior longer-duration memory retention through their separate forget and input gates. This architectural design is particularly effective in complex sequence modeling tasks, wherein both the computational efficiency and robust memory retention are of utmost importance. The ability of this framework to balance the processing speed and memory depth is making it valuable for applications requiring real-time performance without any compromise on the learnability of the extended temporal patterns. This hybrid GRU-LSTM framework can help to obtain improved accuracy and maintain a reasonable computational overhead compared to the usage of multiple LSTM layers.

The hybrid GRU-LSTM framework-based SOC estimation takes place by combining computational efficiency with superior memory retention capabilities. This architectural combination can address the battery charge behavior's dual nature that could involve immediate voltage-current relationships and slower patterns that evolve across the extended cycles. The hybrid GRU-LSTM framework-based SOH estimation takes place by addressing the battery degradation patterns across multiple timescales in a simultaneous fashion. The framework can process short-term performance variations through GRU's streamlined gating mechanism, and it can preserve the critical long-term degradation trends with the inclusion of LSTM. Note: The three methods like linear regression, GRU, and GRU-LSTM were used for predicting both SOC and SOH, that serves the dual purpose.

The critical facts of GRU-LSTM Hybrid are as follows:
- Framework: Keras + TensorFlow backend
- Architecture: Input layer → GRU layer (64 units) → LSTM layer (32 units) → Dense layer → Output
- Activation: tanh (hidden), linear (output)
- Optimizer: Adam (learning rate = 0.001)
- Loss: mean squared error (MSE)
- Epochs: 100; Batch Size: 32
- Purpose: Combine GRU's computational efficiency with LSTM's long-term memory capabilities to model both short-term fluctuations and long-term trends in battery behavior
- Advantage: Balanced trade-off between speed and memory depth, ideal for scenarios with complex sequential patterns over extended cycles.

2.6. Web interface implementation and its modules

The dual-model system was deployed as a web application.
- For the backend: i) Developed using flask (python); ii) Exposes /predict-soc and /predict-soh endpoints; iii) Loads serialized.pkl models using joblib.
- For the frontend: i) HTML/CSS for structure and styling; ii) JavaScript for form validation and dynamic result display; iii) Users can manually enter: voltage, current, temperature, and cycle count; iv) output is displayed as SOC (%) and SOH (%) in real-time.

Now, we briefly denote the implementation modules of our work concerned with computing battery SOC and SOH with state-of-the-art methodologies.

2.6.1. System

Handles the core logic for SOC and SOH prediction.
- SOC Model: Uses linear regression, RNN, stacked LSTM, GRU, and GRU-LSTM to estimate battery charge.
- SOH Model: Uses linear regression, Stacking regressor, TPOT regressor, GRU, and GRU-LSTM to estimate battery health.
- Preprocessing: Normalizes input data for accurate predictions.
- API: Flask-based backend receives input, runs models, and returns results.

2.6.2. User

Interface for data input and result display.
- Input: User enters battery sensor data via form or file upload.
- Display: Shows SOC and SOH predictions with visual indicators.
- Validation: Ensures correct data input and handles errors.
- Tech Stack: Built with HTML, CSS, and JavaScript for easy interaction.

2.7. Advantages

Now, let us look at the probable advantages that can drawn out of our work in the following bulletins:
- Provides practical-sense estimation of both SOC and SOH with the deployment of data-driven models.
- Adapts to different battery types through retraining on new datasets.
- Eliminates the need for battery-specific modeling and parameter tuning.
- Offers a web-based interface for ease of use by non-technical users.
- Ensures high accuracy and robustness via hybrid deep learning models.

- Allows easy integration with existing BMS.
- Supports future scaling with IoT sensors and online retraining mechanisms.

3. RESULTS AND DISCUSSION

3.1. Overview of evaluation metrics

All models were evaluated using the following standardized metrics: i) R^2 score (coefficient of determination), ii) mean absolute error (MAE), iii) MSE, iv) root mean squared error (RMSE). Metrics were calculated separately for test datasets. These were used for model selection, and visual comparisons were made using matplotlib regression cycle plots.

3.2. Results obtained

The battery SOC and SOH are computed with various state-of-the-art methodologies. The results are obtained separately for each of those methodologies and the evaluation metrics are compared with each other in this section. The actual and predicted battery cycle calculated by the RNN regression technique is given in Figure 2. The curves are plotted against the battery capacity values. The actual and predicted battery cycle calculated by the stacked LSTM regression technique is denoted in Figure 3. The curves are plotted against the battery capacity values.

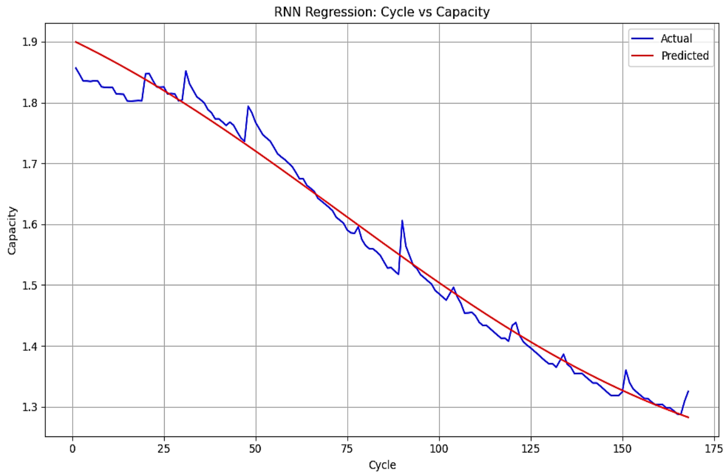

Figure 2. RNN regression cycle comparison

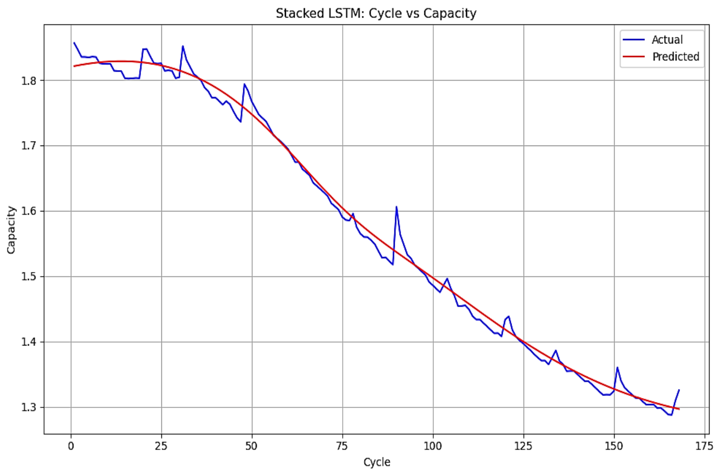

Figure 3. Stacked LSTM regression cycle comparison

The actual and predicted battery cycle calculated by the stacking regressor technique is indicated in Figure 4. The curves are plotted against the battery capacity values. The actual and predicted battery cycle calculated by the TPOT regressor technique is shown in Figure 5. The curves are plotted against the battery capacity values. Figure 5 shows that the capacity (as per TPOT regressor) over time decreases from approximately 1.0 to near 0.1 over roughly 120-time units, following the characteristic downward-curving pattern.

The actual and predicted battery cycle calculated by the linear regression technique is represented in Figure 6. The curves are plotted against the battery cycle count in x-axis and battery capacity values in y-axis. It indicates that battery capacity decline follows to a predictable trend. The actual and predicted battery cycle calculated by the GRU regression technique is represented in Figure 7. The curves are plotted against the battery cycle count and battery capacity values in the x-axis and y-axis respectively. GRU- methodology exhibits enhanced performance for battery condition assessment and residual lifespan forecasting. It shows how battery capacity can decrease from approximately 1.85 to 1.3 over 175 charge-discharge cycles, with the close alignment between the blue (actual) and red (predicted) lines indicating the performance of GRU model in predicting the nonlinear capacity fade pattern. Furthermore, Figure 7 shows that the actual and predicted curves cross each other, meaning that GRU can accurately predict the capacity over the increase of cycles.

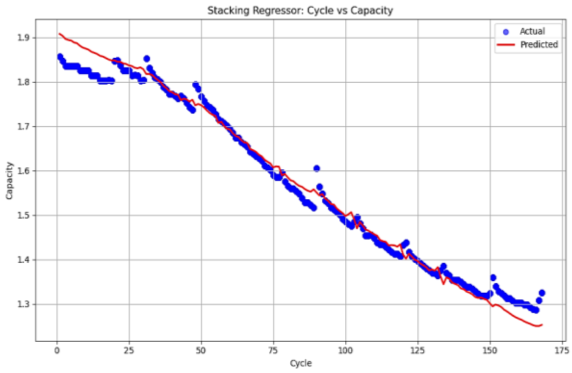

Figure 4. Stacking regressor cycle comparison

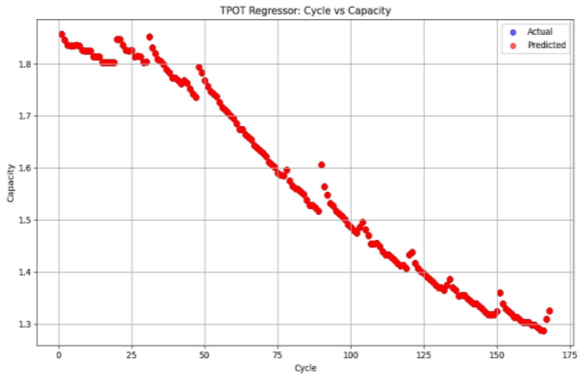

Figure 5. TPOT regressor cycle comparison

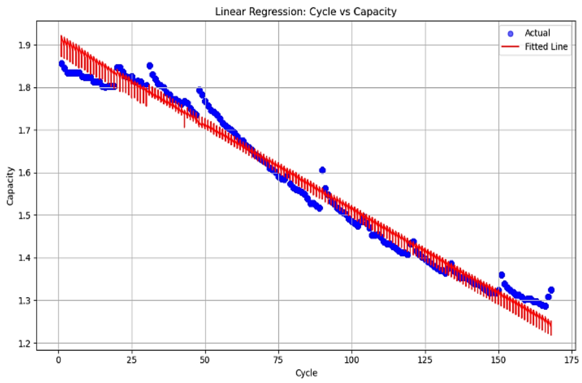

Figure 6. Linear regression cycle comparison

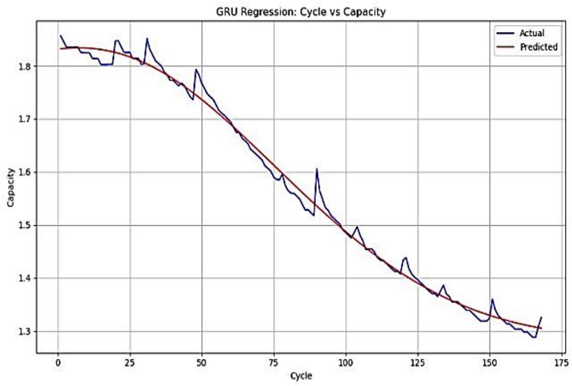

Figure 7. GRU regression cycle comparison

The actual and predicted battery cycle calculated by the GRU-LSTM technique is represented in Figure 8. The curves are plotted against the battery capacity values. The curves are plotted against the battery cycle count and battery capacity values in the x-axis and y-axis correspondingly. The hybrid methodology represents a sophisticated approach for battery condition forecasting, providing enhanced precision for residual lifespan assessment and proactive maintenance implementations in power storage technologies. It indicates the performance of GRU-LSTM technique in predicting battery capacity degradation over 175 charge-discharge cycles with the capture of the complex nonlinear decline from approximately 1.85 to 1.3 capacity units. Furthermore, Figure 8 shows that the actual and predicted curves cross each other, meaning that GRU-LSTM can accurately predict the capacity over the increase of cycles. The evaluation metrics of the RNN, stacked LSTM, Stacking, TPOT, linear regression, GRU regression, and GRU-LSTM techniques are tabulated in Table 1.

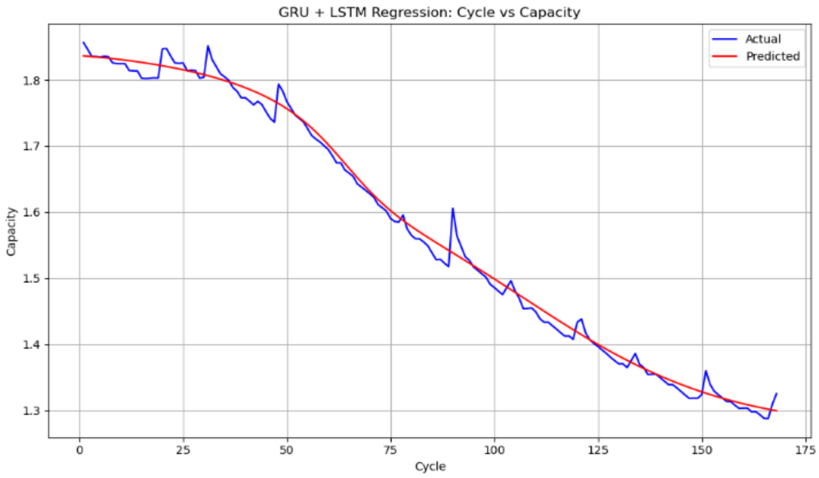

Figure 8. GRU-LSTM regression cycle comparison

Table 1. Evaluation metrics comparison of various regression techniques

Regression model	R-squared	Mean absolute error MAE	Mean squared error MSE	Root mean squared error RMSE
RNN regression	0.9835	0.0181	0.0005	0.0234
Stacked LSTM regression	0.9935	0.0112	0.0002	0.0147
Stacking regressor	0.9819	0.0183	0.0006	0.0246
TPOT regressor	1.0000	0.0000	0.0000	0.0000
Linear regression	0.9770	0.0232	0.0008	0.0277
GRU regression	0.9921	0.0119	0.0003	0.0162
GRU-LSTM	0.9935	0.0115	0.0002	0.0147

3.3. Interpretation of findings

While the paper provides an extensive technical implementation of multiple machine learning and deep learning methodologies for estimating the SOC and SOH of lithium-ion battery packs, a critical discussion is essential to interpret the significance of the findings and their broader impact. The results indicate that among the models tested:

- TPOT regressor achieved perfect accuracy ($R^2 = 1.0$) with zero error metrics, suggesting that automated machine learning pipelines can outperform manually configured models, especially for highly non-linear or complex degradation patterns in SOH prediction.
- Stacked LSTM outperformed other models for SOC estimation with high R^2 (0.9935) and low RMSE (0.0147), validating the effectiveness of deep temporal learning in capturing intricate charge-discharge cycles.
- GRU demonstrated strong performance with $R^2 = 0.9921$ and RMSE = 0.0162, proving its effectiveness in modeling sequential SOC data using fewer parameters, which makes it efficient for real-time applications with limited computational capacity.
- GRU-LSTM hybrid model matched the stacked LSTM in performance, achieving $R^2 = 0.9935$ and RMSE = 0.0147, while combining the benefits of GRU's fast convergence and LSTM's long-term memory capabilities, making it robust for both SOC and SOH estimation tasks.
- Linear regression, while simple and interpretable, showed comparatively higher error rates, confirming that linear models are best suited only for ideal, steady-state battery behavior.

These findings support the notion that no single model is universally optimal, and the nature of the problem (e.g., temporal vs. degradation-focused) dictates the model choice.

3.4. Comparative strengths of the proposed hybrid approach

Compared to conventional techniques such as EKF, electrochemical impedance spectroscopy, and physics-based modeling:

- Our data-driven approach requires no deep battery-specific knowledge or physical equations, making it generalizable across battery types.
- It is modular and scalable, allowing SOC and SOH to be computed using separate specialized models, which improves robustness.
- The use of AutoML (TPOT) eliminates the manual tuning process, reducing development time and improving reproducibility.
- The inclusion of GRU provides a lightweight alternative to LSTM with faster training times and fewer parameters, making it ideal for real-time SOC estimation on edge devices.
- The GRU-LSTM hybrid model combines the computational efficiency of GRU with the long-term memory retention of LSTM, offering superior performance for capturing both short-term variations and long-term battery degradation trends.

Furthermore, the frontend integration via a responsive web interface sets this work apart from many academic-only implementations, pushing it closer to real-world deployment.

3.5. Ramifications and real-world relevance

The implications of this work are substantial for several application domains:

- EVs: Reliable SOC/SOH estimation prevents range anxiety, ensures longer battery life, and enhances user safety.
- Grid-scale energy storage: Accurate predictions support better charge scheduling, load balancing, and capacity planning.
- Battery-as-a-Service (BaaS) platforms: The framework can serve as a plug-and-play diagnostic tool in battery leasing, warranty assessment, and lifecycle prediction.
- Consumer electronics: Lightweight models like linear regression or RNN can be embedded into IoT devices for health monitoring without needing cloud computation.

3.6. Evidence-based evaluation of results

The results section further demonstrates analytical thinking:

- Evaluation metrics (R^2, MAE, MSE, RMSE) are not just shown—they are compared across models to determine fitness for purpose.
- The perfect score of TPOT regressor ($R^2 = 1.0$) is not accepted blindly—it is interpreted as a strength of automated pipeline optimization, particularly for noisy and high-dimensional SOH data.

3.7. Broader implications

This analytical lens reveals several broader implications for the field of battery diagnostics and smart energy systems:

- Models like stacked LSTM and GRU-LSTM are not only technically advanced but also practically viable in real-world scenarios such as EV acceleration cycles, where capturing both short-term fluctuations and long-term degradation trends is essential.
- The GRU model, with its simpler architecture and faster training time, proves highly effective for resource-constrained applications, enabling accurate SOC estimation with reduced computational overhead.
- The exceptional performance of the TPOT regressor indicates a paradigm shift toward automated, self-optimizing systems that can evolve as new battery data becomes available eliminating the need for extensive manual tuning.

This paper does more than just compare models—it critically evaluates their suitability for specific aspects of battery behavior. By highlighting where traditional and even some deep learning models fall short, and demonstrating how a hybrid approach combining GRU, GRU-LSTM, LSTM, and AutoML can overcome these limitations, the work advances the domain of intelligent battery management. It promotes a scalable, real-time, and interpretable solution backed by solid empirical evidence and aligned with practical deployment needs. The study underscores not just performance metrics, but contextual suitability—providing deeper insights into which models are most appropriate for SOC and SOH prediction under varying operational demands.

4. CONCLUSION

This research successfully constructs a hybrid deep learning-based system for estimating the SOC and SOH of battery in an accurate manner, thereby addressing a critical need in EVs and energy storage system management. By employing distinct models tailored to each task—linear regression, RNN, and stacked LSTM for SOC, and stacking regressor and TPOT regressor for SOH—we were able to effectively leverage the unique characteristics of two different datasets. Furthermore, we used other two methodologies, namely, GRU regression, and GRU-LSTM techniques for further improvement. This separation ensured model precision and robustness across both battery state parameters. The dual-model design facilitates real-time prediction capabilities through a responsive web interface built using HTML, CSS, and JavaScript, while backend processing is handled via Python-based machine learning frameworks. We do the processing of user-provided inputs like temperature, current, voltage, and battery cycle count for the sake of delivering an instant SOC and SOH estimations. This makes our system more practical and user-friendly. The prediction outcomes of SOH have been optimized by including the TPOT, which reveals the AutoML prospects in real-world energy applications. At the outset, the hybrid architecture that we have proposed in this work is contributing significantly towards the smarter BMS with the enhancements made to the operational reliability and improved safety standards. This can eventually extend the battery lifespan with well-informed decisions and predictive insights.

The future extension of this hybrid deep neural network approach- estimating the SOC and SOH of battery, is possible with the integration of real-time IoT connectivity. This will enable live data streaming in the BMS that has been deployed in EVs or energy storage units. With the enabling of such live data streaming functionality, it will be possible to develop a fully automated and dynamic prediction capabilities-backed system that can eliminate the dependency on manual data input. Furthermore, the adapting potential of the design can be enhanced with the implementation of transfer learning or continual learning methodologies, which allows for the generalization across various battery chemistries, manufacturers, and operating conditions using minimal retraining. The other promising direction to proceed with the investigation is the fusion of additional parameters such as temperature, humidity, and charge-discharge cycles to boost prediction accuracy and model robustness. For assuring the scalability of the system, introduction of renowned cloud deployment platforms like AWS or Azure and integration of mobile app can be done to handle large-scale battery-operated vehicles and facilitate portable monitoring, respectively. Looking at another future research perspective of integrating explainable AI (XAI) techniques. This integration will render the predictions to be more transparent and trustworthy, suiting the safety-critical applications. At last, we look at the prospect that could be yielded with the inclusion of anomaly detection modules. This inclusion can enable early warning systems for battery degradation or failure, which can further support the preventive maintenance and paves the way towards the significant extension of battery life. All the aforesaid enhancements have the potential to transform our system into a next-generation solution that can offer intelligent battery diagnostics and energy management.

Several components of this research hold significant potential for future expansion and practical deployment:

i) IoT integration: By enabling real-time data ingestion from BMS, the framework can evolve into an intelligent edge diagnostic solution capable of continuous monitoring and rapid response.
ii) Transfer and federated learning: The trained models can be adapted across various battery chemistries and usage environments with minimal retraining, enhancing scalability and reducing the dependency on large, annotated datasets.
iii) Explainable AI (XAI): Incorporating interpretability tools will foster transparency, helping engineers and end-users understand model predictions—especially vital for safety-critical applications like EVs and grid storage.
iv) Anomaly detection: With minor extensions, the system can be upgraded to detect early warning signs of battery faults, such as thermal events, internal shorts, or capacity drop-offs.

This work establishes a robust foundation for future-ready, scalable battery diagnostics. The hybrid modeling strategy ensures adaptability, the modular SOC/SOH pipelines enhance precision, and the integration of AutoML and a user-friendly frontend bridges the gap between academic research and real-world application. Most importantly, architecture supports future enhancements through continuous learning and system-level upgrades in smart energy ecosystems.

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C : **C**onceptualization
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E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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