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Review

A Review of AI Applications in Lithium-Ion Batteries: From State-of-Health Estimations to Prognostics

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Abstract

Battery management systems (BMSs) are integral components of electric vehicles (EVs), as they ensure the safe and efficient operation of lithium-ion batteries. State of health (SoH) estimation is one of the core functions of BMSs, providing an assessment of the current condition of a battery, while prognostics aim to predict remaining useful life (RUL) as a function of the battery's condition. An accurate SoH estimation allows proactive maintenance to prolong battery lifespan. Traditional SoH estimation methods can be broadly divided into experiment-based and model-based approaches. Experiment-based approaches rely on direct physical measurements, while model-driven approaches use physics-based or data-driven models. Although experiment-based methods can offer high accuracy, they are often impractical and costly for real-time applications. With recent advances in artificial intelligence (AI), deep learning models have emerged as powerful alternatives for SoH prediction. This paper offers an in-depth examination of AI-driven SoH prediction technologies, including their historical development, recent advancements, and practical applications, with particular emphasis on the implementation of widely used AI algorithms for SoH prediction. Key technical challenges associated with SoH prediction, such as computational complexity, data availability constraints, interpretability issues, and real-world deployment constraints, are discussed, along with possible solution strategies.

Keywords: lithium-ion battery; state of health; battery management system; electric vehicle; artificial intelligence; machine learning; deep learning; prognostics; energy storage system

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1. Introduction

Transport accounts for 25% of annual global carbon emissions [1]. Given mounting concerns over air pollution, transitioning away from fossil-fuel-based vehicles to electric vehicles (EVs) has become a pivotal component in creating a low-carbon future [2]. Governments worldwide have instituted policies and incentives that encourage the adoption of EVs, leading to significant growth in global sales since 2018, as shown in Figure 1 [3]. However, this rapid adoption has also increased demands for high-performance, long-lasting battery systems [4,5].

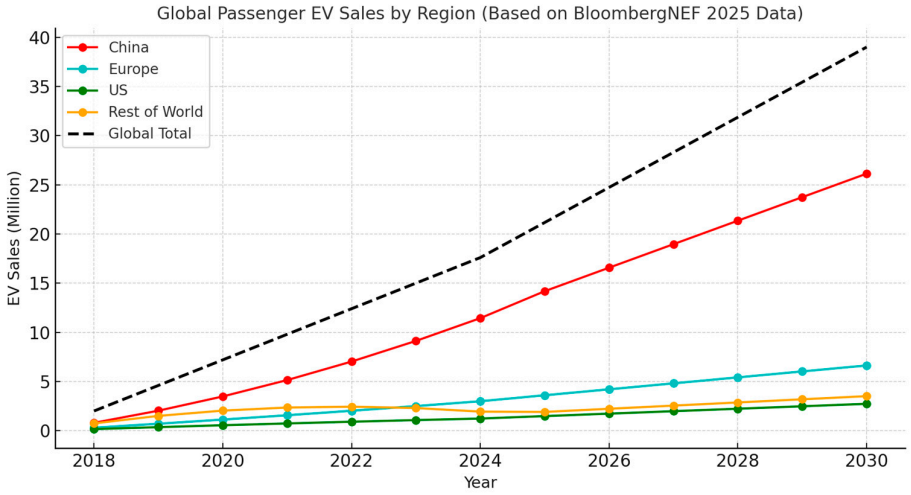

Figure 1. Annual passenger-car and light-duty vehicle sales in major regions, illustrating historical trends and near-term projections, adapted from [3].

Lithium-ion (Li-ion) batteries have become the dominant energy storage technology for EV applications due to their high energy density, lightweight characteristics, and declining production costs [6]. Despite these advantages, Li-ion batteries experience capacity degradation over time, which directly impacts vehicle performance, driving range, and overall battery lifespan. Battery degradation is influenced by multiple factors, including temperature, charging cycles, and discharge rates; therefore, accurate estimation of the state of health (SoH) is essential to battery safety, maintenance planning, and efficient energy management [7–11].

Battery management systems (BMSs) play a critical role in monitoring and controlling battery operation by estimating metrics such as state of charge (SoC) and SoH [8]. SoH estimation provides insight into battery aging and supports the prediction of remaining useful life (RUL), serving as an early indicator of replacement needs or potential safety hazards [7,12,13]. Traditional SoH estimation techniques rely on either experimental testing or model-based approaches [14–16]. Experimental methods depend on controlled laboratory testing, which is costly and time-consuming, while model-based approaches—such as electrochemical or statistical models—often exhibit limited generalizability and reduced accuracy under real-world EV operating conditions [12,17].

Artificial intelligence (AI) and machine learning (ML) methods have advanced rapidly, making AI-driven SoH prediction increasingly prominent in recent years [18,19]. Sequence models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are well suited for capturing temporal dependencies in battery cycling data. In parallel, feed-forward neural networks (FFNNs), such as multilayer perceptrons, remain strong baseline models when temporal information is embedded into fixed-length feature representations (e.g., windowed charge/discharge profiles or incremental capacity features). Across these model families, nonlinear function approximation enables the learning of complex relationships among voltage, current, temperature, operational protocols, and degradation indicators, supporting accurate near-real-time SoH prediction [20–22].

Recent developments in deep learning have further expanded the capabilities of battery health prediction frameworks. Transformer-based models have shown strong potential in capturing long-term dependencies and complex temporal behaviors of Li-ion battery degradation data, often outperforming traditional RNN-based models [23–25]. This aligns with broader trends in battery prognostics, including RUL prediction, that advocate hybrid architectures combining convolutional, recurrent, and attention mechanisms to fuse multivariate sensor data. Additionally, explainable AI (XAI) techniques are increasingly

applied to enhance model transparency and interpretability, which is particularly important for safety-critical EV battery management systems and regulatory compliance [26]. Despite these advances, AI-based SoH prediction still faces a fundamental challenge common to many data-driven approaches: the scarcity of high-quality, long-term degradation datasets that fully represent real-world operating conditions. Limitations, such as incomplete life-cycle data, distribution shifts between laboratory and field conditions, and data imbalance, hinder the deployment of AI models beyond theoretical or experimental studies [27–29].

Parallel to these developments, digital twin frameworks have emerged as a promising paradigm for real-time battery diagnostics and prognostics, enabling dynamic interaction between physical batteries and their virtual counterparts [30]. Such approaches support higher-fidelity predictions and contribute to improved safety, cost efficiency, and extended battery lifespan [23].

This review provides a comprehensive assessment of recent advances in AI-based SoH estimation techniques. Specifically, it summarizes and compares existing AI models in terms of prediction accuracy and computational efficiency, while also discussing implementation challenges associated with deployment in EV battery systems.

Contribution and Organization of This Review

Several reviews have previously addressed SoH estimation for Li-ion batteries. Earlier studies, such as that of Lin et al. [17], focused primarily on experimental and physics-based models, while more recent reviews, including those of Sylvestrin et al. [31] and Guirguis and Ahmed [23], examined a broad range of data-driven methods encompassing machine learning and transformer-based models. Other works have emphasized digital twin frameworks [30] or hybrid neural networks [21]. However, many existing reviews are limited in scope, lack systematic comparison across datasets, or provide minimal discussion of evaluation metrics and practical deployment considerations.

This review distinguishes itself by offering a broad and systematic synthesis of AI-based SoH prediction methods, spanning traditional machine learning, deep learning, and transformer architectures. Comparative benchmarking is presented based on reported results from widely used public datasets, including NASA [32], CALCE [33], and Oxford [34]. In addition, this review discusses evaluation metrics related to practical battery management applications and identifies critical issues such as data quality, model interpretability, and transfer-learning difficulties. By connecting methodological advances with practical considerations, this review not only summarizes recent progress but also outlines a pathway toward accurate, interpretable, and deployable AI models for SoH prediction.

The remainder of the paper is organized as follows: Section 2 defines SoH and reviews AI-based methods; Section 3 describes workflow, benchmark datasets, and evaluation metrics; Section 4 compares representative AI methods; and Section 5 provides a summary of challenges, open issues and future research directions.

2. AI-Based Methods for SoH Prediction

2.1. Definition of State of Health (SoH)

SoH is an important metric used to determine the deterioration state of a Li-ion battery based on its initial state [17,35,36]. In most cases, the SoH is conceptually defined in regard to capacity fade: the ratio between the current maximum available capacity ($C_{current}$) and the rated initial capacity (C_{rated}):

$$SoH = \left(\frac{C_{current}}{C_{rated}} \right) \times 100\%$$

This definition of SoH may be calculated based on the present charge storage potential of the battery as compared against its nominal design value, or from measured internal resistance or power capability, where increased resistance or decreased peak power give another measure of degradation, and the two measurements may yield different values of SoH [9]. However, in either formulation, the decreasing SoH value represents the worsening battery state, and decreasing usable lifetime. Generally, BMSs use SoH to monitor a cell or pack RUL, provide early warnings of impending failures, and inform all operational procedures (i.e., schedule maintenance, charging control, warranty management) [17]. Therefore, accurate SoH estimation is critical to extend battery life, safety, and enable the reliable use of EVs and grid-connected energy storage.

As AI-driven approaches continue to advance, various methods have been developed to improve SoH estimation accuracy [37]. These methods can be broadly categorized into traditional machine learning techniques, deep learning models, transfer learning and self-supervised learning, and hybrid AI-physics-based approaches. Each method offers unique advantages and challenges in handling battery degradation prediction.

2.2. Traditional Machine Learning Methods

Traditional machine learning methods involve statistical models that can analyze past battery data and predict future SoH based on patterns found in historical data [31]. Some of the most commonly used traditional machine learning algorithms include those outlined below.

2.2.1. Support Vector Machines (SVMs)

Support vector machine is based on statistical learning theory. This model is used for classification and regression tasks. It was proposed by Vapnik et al. [38]. The core idea of SVM is to find an optimal hyperplane to separate data points of different categories and maximize the distance (i.e., "margin") from this hyperplane to the nearest data point (support vector) (shown in Figure 2) [39].

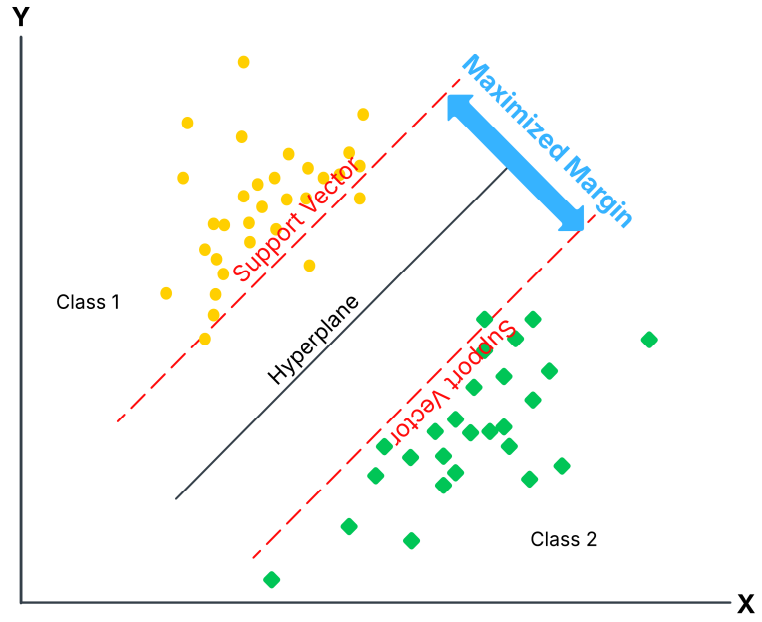

Figure 2. Maximum margin and hyperplane for an SVM trained using samples from two classes. The samples on the margin are called support vectors, adapted from [39].

There are two main forms of SVM [38,39]: Classification SVM—used to distinguish categories, such as judging whether the battery is healthy—and regression SVM (SVR)—

used to predict continuous values, such as the specific value of the battery SoH. Because SoH is a continuous numerical indicator, SVR is usually used to represent the percentage of the current capacity of the battery relative to the initial capacity. SVM collects key parameters, such as current change, battery temperature, voltage curve during charging, etc. from the BMS [9]. By optimizing a convex quadratic programming problem, it finds the support vector and the optimal hyperplane to fit the relationship between the input features and SoH. Once the model is successfully trained, the trained SVM model is embedded in the BMS, and the battery data are input in real time to predict the SoH value [31,40,41].

SVM can effectively capture the complex nonlinear relationship in battery degradation. However, when the amount of data is large (such as battery data running for a long time), SVM training time is long. Not only that, SVM is very dependent on the quality of the input features. If the feature extraction is not appropriate, the prediction accuracy will decrease.

2.2.2. Random Forest (RF)

Random forest (RF), introduced by Breiman in 2001 [42], is an ensemble learning algorithm that improves predictive accuracy and model robustness by integrating the outputs of multiple decision trees (see Figure 3). In the context of Li-ion battery prognostics, RF has demonstrated high effectiveness in estimating both the SoH and RUL.

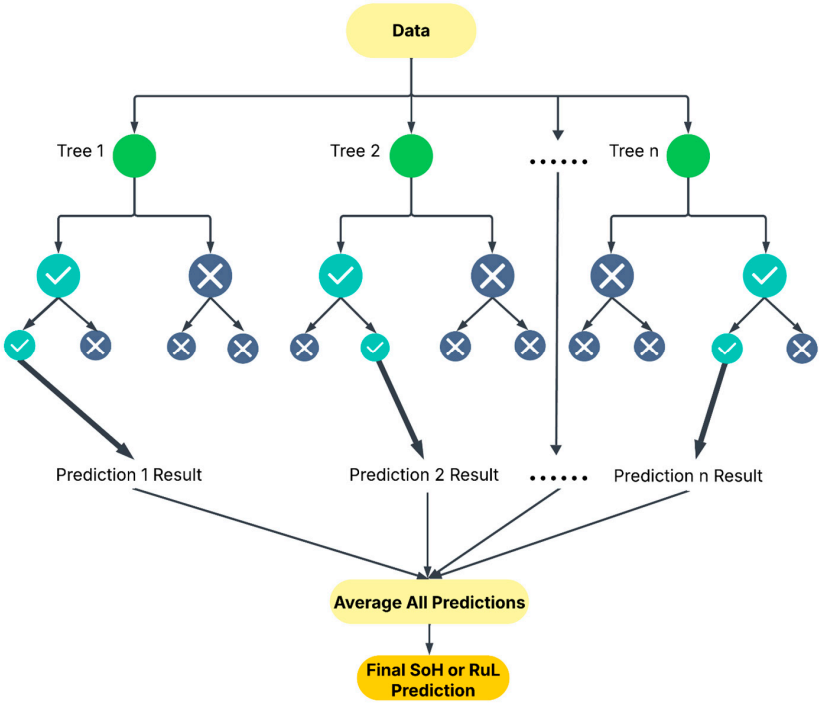

Figure 3. Structure of the random forest (RF) algorithm. Each decision tree is trained on a random subset of the data. Final output is determined by majority voting (for classification) or averaging (for regression), adapted from [43].

As illustrated in Figure 3, the RF algorithm begins with the generation of multiple decision trees, each trained on a different bootstrap sample of the original dataset. To reduce the correlation among trees and enhance generalization, RF employs random feature selection at each decision node during tree construction. For regression problems, such as SoH estimation, the final prediction is obtained by averaging the outputs of all individual trees, which can be mathematically expressed as follows:

$$\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} T_i(X)$$

where $\hat{Y}$ is the predicted SoH value, N is the total number of decision trees, $T_i(X)$ denotes the output of the i-th tree for input features X, and X includes sensor data such as voltage, current, temperature, internal resistance, and cycle count.

The RF approach is particularly suitable for modeling the complex, nonlinear degradation behaviors inherent in Li-ion batteries. Unlike deep learning methods, RF requires less training data and offers better interpretability, while also being robust to noise and missing values. Additionally, RF can evaluate feature importance, aiding in the identification of key indicators of battery aging.

In SoH estimation tasks, RF provides a balance between prediction accuracy and computational efficiency, making it an attractive solution for implementation in BMSs and edge computing environments.

RF remains a robust ensemble method frequently employed in battery SoH estimation due to its ability to handle nonlinear relationships and large, noisy feature sets while providing feature importance insights. Recent progress includes convolutional neural network-RF (CNN-RF) hybrid architectures that extract indicators through CNNs and fuse them via RF, enhancing estimation robustness under partial discharge conditions [44]. Other studies have optimized RF models by integrating incremental capacity curve (ICC) features, which improves online degradation tracking and prediction accuracy [45]. In second-life battery applications, RF-based grouping techniques provide rapid SoH estimation without requiring full discharge cycles, facilitating efficient repurposing of retired EV packs [46]. Comparative research demonstrates that RF often outperforms conventional regression methods for SoH, with improved fidelity across diverse datasets [47]. These enhancements underscore RF's versatility, interpretability, and reliability in modern BMS prognostic systems.

2.3. Probabilistic Machine Learning and Digital Twin-Enhanced Prognostics

Recent developments in battery prognostics increasingly leverage probabilistic models like Gaussian process regression (GPR), which not only provide accurate SoH forecasts but also quantify uncertainty—an essential safety feature for EV battery systems [36]. Recent studies have refined GPR approaches with innovations such as GPR combined with incremental capacity analysis (ICA) to extract more robust health features [48] and multi-output GPR to improve battery pack-level trajectory predictions [49]. Simultaneously, digital-twin-based architectures are gaining traction by blending virtual representations with real-time sensing, enabling adaptive SoH assessment even during partial discharge cycles [30]. Building on that, frameworks that integrate explainable AI within digital twins are beginning to emerge—improving diagnostic transparency and fostering trust in BMS prognostic outputs [26]. These innovations point to a shift toward hybrid forecasting frameworks that combine probabilistic modeling, real-time digital replication, and interpretability, enriching BMS functionality beyond traditional machine learning techniques [17,26,30,31,35].

2.4. Deep Learning Methods

2.4.1. Multilayer Perceptron (MLP)

The multilayer perceptron (MLP) is a foundational deep learning architecture widely employed in regression tasks, including Li-ion battery SoH estimation. As illustrated in Figure 4, an MLP consists of three primary components: an input layer, one or more hidden layers, and an output layer. Neurons are fully connected between adjacent layers (each unit connects to all units in the next layer).

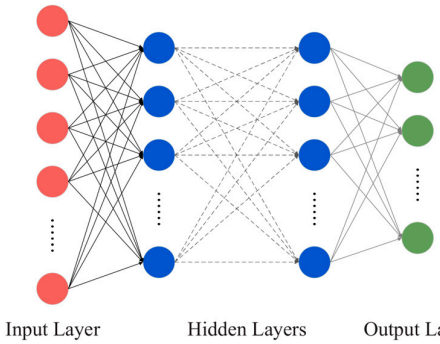

Figure 4. Basic multilayer perceptron (MLP) mechanism, adapted from [50].

Let $h^0 = x$ be the input and index layers $l = 1, \ldots, L$. Each neuron in a hidden layer performs a linear transformation followed by a nonlinear activation. This process can be mathematically expressed as follows:

$$z^l = W^l h^{l-1} + b^l$$
$$h^l = \sigma\left(z^l\right)$$

where z^l denotes the pre-activation output at the l-th layer, $W^l \in \mathbb{R}^{n_l \times n_{l-1}}$ is the weight matrix, $b^l \in \mathbb{R}^{n_l}$ is the bias vector, and σ is a nonlinear activation function such as rectified linear unit (ReLU) or sigmoid. The output layer computes as follows:

$$\hat{y} = g\left(W^L h^{L-1} + b^L\right),$$

with g typically the identity for regression (or a bounding function if constraining SoH to $[0, 1]$).

MLPs learn a mapping from multidimensional input features—such as voltage, current, temperature, and internal resistance—to a scalar SoH output. The model is optimized through backpropagation by minimizing a loss function, commonly the mean squared error (MSE):

$$\mathrm{MSE} = \left(\frac{1}{\mathrm{n}}\right) \sum_{\{\mathrm{i}=1\}}^{\mathrm{n}} (\hat{\mathrm{y}}_\mathrm{i} - \mathrm{y}_\mathrm{i})^2$$

The MLP model offers simplicity, fast training, and effectiveness for non-sequential data, making it a practical choice for real-time battery health monitoring. However, its inability to capture temporal dependencies and sensitivity to feature scaling may limit its applicability in scenarios involving long-term battery degradation trends sensitive to data normalization and hyperparameter configuration.

MLP remains a prevalent choice in SoH estimation due to its simplicity, efficiency, and capacity to model nonlinear relationships in fixed-size feature sets. Flexible MLPs have recently been employed to estimate SoH from partial charging curves, achieving root mean squared error (RMSE) below 1.5%, even across varying battery types and sampling scenarios [51]. Feature-fusion approaches combining principal component analysis (PCA) and optimization algorithms like the grey wolf optimization (GWO) have enhanced MLP generalization and stability for voltage-derived inputs [52]. In addition, patch-based and multi-scale MLP frameworks—notably multi-scale patch-based MLP (MSPMLP)—capture both global degradation trends and local regenerative phenomena, offering significant accuracy gains, with mean absolute error (MAE) improved by ~41.8% on public datasets such as NASA [53]. Further, interpretable MLP configurations using ensemble decision boundary visualizations have improved transparency in SoH decision-making [14]. Beyond data-driven structures, physics-informed MLPs that embed degradation dynamics and

physical constraints as part of their architecture are emerging, demonstrating robustness and fidelity in SoH forecasting [54].

2.4.2. Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) are neural networks designed for sequential data, making them well suited to time-series problems such as Li-ion battery SoH estimation. In contrast to feedforward networks such as MLPs, RNNs maintain an internal hidden state that is updated at every time step. This vanilla RNN structure, as shown in Figure 5, enables the model to retain temporal context, which is crucial for learning degradation trends in batteries across multiple charge/discharge cycles.

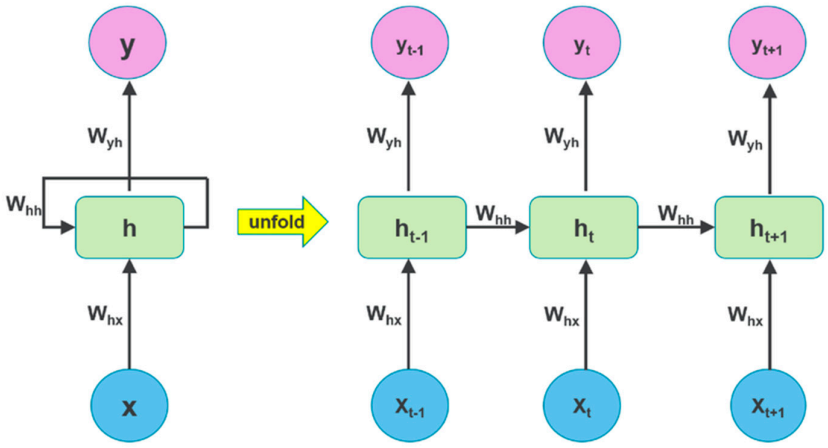

Figure 5. Structure of a simple unfolded RNN layer [55].

Let $x_t \in \mathbb{R}^{n_x}$ be the input vector at time t, $h_t \in \mathbb{R}^{n_h}$ be the hidden state, and y_t the output. A standard (vanilla) RNN (see Figure 5) updates as follows:

$$h_t = \sigma(W_{xh}x_t + W_{hh}h_{t-1} + b_h), y_t = g\Big(W_{hy}h_t + b_y\Big),$$

where σ is typically tanh or ReLU, g is identity for regression, $W_{xh} \in \mathbb{R}^{n_h \times n_x}$, $W_{hh} \in \mathbb{R}^{n_h \times n_h}$, $W_{hy} \in \mathbb{R}^{n_y \times n_h}$, and b_h, b_y are bias terms.

RNNs remain central to Li-ion battery SoH prediction thanks to their dynamic sequence modeling capabilities. Beyond vanilla RNNs, advanced variants like dual-stage attention RNN (DARNN) have been introduced to enhance feature extraction and attention weighting in degradation modeling. Teixeira et al. applied a variant of RNN, gated recurrent unit (GRU) to accurately model battery SoH evolution in smartphone battery swap systems, highlighting the feasibility of RNNs in practical SoH tracking tasks [56]. Similarly, another study proposes an improved GRU model that streamlines feature representation for accurate SoH estimation [57]. Additionally, the GRU–battery performance predictor (GRU-BPP), which integrates physical priors, PCA, and clustering for feature selection, enhances both accuracy and interpretability in battery SoH prediction [58]. Large-scale applications of bidirectional GRU (BiGRU) models optimized by sparrow search algorithms on driving-condition datasets (e.g., Oxford battery data) have demonstrated robust and generalizable SoH predictions in real EV environments [59]. Furthermore, a multi-input metabolic GRU (MM-GRU) structure designed for retired Li-ion packs, provides accurate and scalable SoH monitoring without full discharge cycles [60]. Recent studies have also explored high-accuracy SoC estimation methods, such as the EBWO-GRU-ACKF framework proposed by Liu et al. [61], which demonstrates the potential of combining optimization algorithms with recurrent networks for battery state estimation, although its target is SoC rather than SoH [61]. These findings underscore the continued evolution of RNN models—

from attention mechanisms to hybrid optimization—thereby extending their relevance and performance across diverse battery-prognostics contexts.

2.4.3. Long Short-Term Memory (LSTM) Networks

Long short-term memory (LSTM) networks are a gated variant of recurrent neural networks designed to model long-range temporal dependencies while mitigating vanishing/exploding gradients [62]. In Li-ion battery health monitoring, the inputs are naturally sequential: BMS time-series signals such as voltage, current, temperature, and derived indicators (e.g., SoC and incremental-capacity/differential-voltage features) evolve over cycles and encode degradation patterns. Figure 6 provides a stylized, self-created schematic that retains the standard LSTM gating mechanism while explicitly highlighting battery-specific inputs x_t and prognostics outputs (e.g., SoH and RUL). At each time step t, an LSTM cell computes the following:

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right), i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

$$\widetilde{C}_t = \tanh(W_C x_t + U_C h_{t-1} + b_C), C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t,$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), h_t = o_t \odot \tanh(C_t).$$

where x_t is the input vector (e.g., battery voltage, current, temperature), h_{t-1} is the previous hidden state, C_t denotes the cell state, σ is the sigmoid activation function, tanh is the hyperbolic tangent, and $\odot$ represents element-wise multiplication. The forget gate f_t controls retention of past information, the input gate i_t regulates incorporation of new information via the candidate $\widetilde{C}_t$, and the output gate o_t exposes part of the cell state to produce h_t.

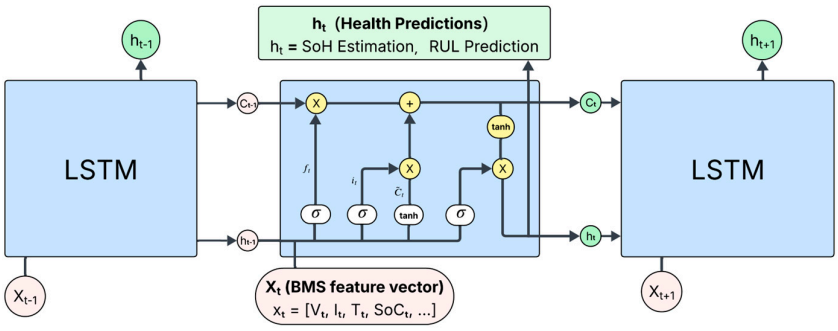

Figure 6. Battery-aware LSTM schematic for Li-ion prognostics. The diagram preserves the standard LSTM cell update (forget gate f_t, input gate i_t, candidate memory $\widetilde{C}_t$, cell state C_t, output gate o_t, and hidden state h_t) while contextualizing the input x_t as a BMS feature vector (e.g., voltage, current, temperature, SoC, and optional differential-voltage/incremental-capacity descriptors). The hidden state h_t can be mapped to application outputs such as state-of-health (SoH) estimation and/or remaining useful life (RUL) prediction for battery management.

In the context of Li-ion battery SoH estimation, the ability of LSTMs to model both short- and long-term temporal dynamics makes them well suited to capturing subtle degradation patterns and capacity fade trends over many cycles. For example, Xu et al. developed an LSTM model augmented with spatio-temporal attention to separate degradation sequences into trend and dynamic components, improving robustness against capacity regeneration and enhancing prediction accuracy [63]. Yao et al. used a double-layer LSTM coupled with grey relation analysis of voltage features to achieve single-cycle SoH predictions with relative errors under 2%, even with small batch data [64].

Furthermore, Zhang et al. introduced a hybrid KAN–LSTM model, where a Kolmogorov–Arnold network (KAN) first extracts key abstract features from multi-dimensional inputs that are then processed by LSTM to capture aging trends—resulting in enhanced computational efficiency and predictive accuracy [65]. Another advanced approach integrates metaheuristic optimization [61,66,67], which proposes a CNN–LSTM–attention– four-vector intelligent metaheuristic (FVIM) model that achieves MAE ≈ 0.99% and RMSE ≈ 1.33% on NASA and University of Maryland datasets by combining convolutional feature extraction, sequential memory, attention mechanisms, and intelligent optimization [68].

Moreover, a multi-BiLSTM fusion model with attention and multi-loss optimization has demonstrated enhanced real-time SoH estimation capabilities by weighing features and losses adaptively across sequences [69]. In addition, CNN-LSTM frameworks exploiting voltage deviation patterns have improved SoH tracking by extracting local patterns that plain LSTMs may overlook [70,71]. Recent studies also extend LSTM-based SoH methods to incorporate ecological cycle decomposition or physics-informed preprocessing to enhance prediction stability under varying cycling conditions [72,73].

Overall, LSTMs adapt to long sequence dependencies, handle complex multi-channel inputs, and can achieve high accuracy across variable charging scenarios. Remaining challenges include model complexity and computational cost—particularly for attention-augmented or hybrid architectures targeted to embedded BMS deployment [74,75].

2.4.4. Transformer

In recent years, attention mechanisms and transformer architecture, as shown in Figure 7, have revolutionized sequence modeling by the capturing of long-range dependencies without resorting to recurrence [23]. At the core of transformer models lies the scaled dot-product attention:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where Q, K, and V are the query, key, and value matrices computed from input embeddings, respectively, and d_k denotes the dimensionality of the key vectors.

This formulation enables the model to dynamically weigh the relevance of different temporal features—a powerful capability for battery SoH prediction, where long-range temporal patterns such as aging behaviors and regeneration events are critical to capture. The attention mechanism illustrated in Figure 7 takes battery management system (BMS) time-series data, which consist of multivariate signals (e.g., voltage, current, and temperature) organized into fixed-length sequences. The time-series data are embedded as a latent representation of the time-series signals. The embedded representations are then processed through the transformer encoder–decoder architecture with the self-attention operation, which enables the model to focus on the informative temporal segments over extended periods (with many segments over an extended time period). Using this attention mechanism, the transformer is able to effectively identify degradation and regeneration trends over many cycles, thereby providing an accurate estimation of the state of health (SoH).

One representative application of this approach is CyFormer, which conceptualizes battery degradation as a cyclic time-sequence problem. CyFormer's encoder employs both row-wise and column-wise attention blocks to extract intra-cycle and inter-cycle features, allowing it to process cycle-by-cycle dependencies more effectively than conventional CNN–RNN frameworks [76]. This model attains a remarkable MAE of 0.75% using only 10% of the data for fine-tuning, demonstrating both accuracy and data efficiency [77].

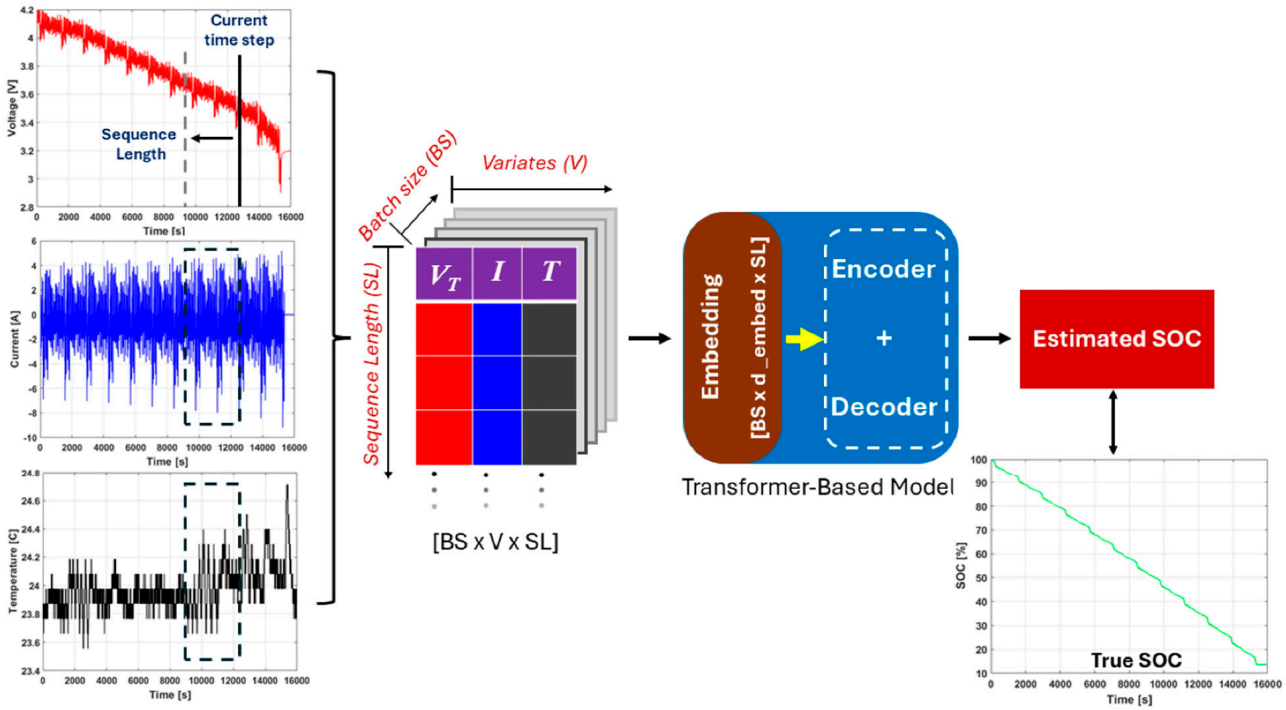

Figure 7. Typical transformer architecture adapted for SoH estimation tasks: embeddings, positional encoding, multi-head attention, and feed-forward networks to process sequential battery features (e.g., voltage, current, temperature).

Another innovative strategy, proposed by Bong Chen et al., adopts a transformer–GRU parallel architecture [24]. By firstly reconstructing noisy features through complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) decomposition and Gaussian filtering of incremental capacity curves, these features are then processed simultaneously by cross-attention in a Transformer branch and by temporal modeling in a GRU branch. The combined outputs yield significantly improved robustness and accuracy in SoH estimation across multiple datasets, reducing RMSE by over 61% compared to baseline methods.

Cai and Liu further integrated transformer attention with LSTM memory in a fusion model. This approach extracts multidimensional features—spanning time, frequency, and state-of-charge dimensions—and leverages attention to focus on critical links while using LSTM to preserve temporal context. Validated on 124 commercial lithium iron phosphate ($LiFePO_4$) battery datasets under fast-charging scenarios, this method demonstrated both high prediction accuracy and excellent generalization [25,78]. The dataset is a large-scale dataset comprising 124 commercial lithium iron phosphate/graphite cells cycled under 72 varied fast-charging protocols, with cycle lives spanning 150 to 2300 cycles [13]. Notably, frequency–domain features may also be effective for identifying degradation patterns. For instance, Liu et al. [79]. introduced a spectral attention mechanism in load forecasting to focus on key frequency components—a strategy that could potentially be adapted to multi-scale voltage signal analysis to enhance SoH feature extraction capabilities [79].

A BiLSTM–transformer hybrid model demonstrated exceptional accuracy (errors < 0.6%) when applied to fast-charging datasets involving 124 commercial lithium iron phosphate cells [80]. Time-series transformer (TST) architectures, including encoder–decoder and hybrid TST–LSTM models, have been shown to effectively incorporate auxiliary environmental and vehicle parameters (e.g., ambient temperature, regenerative braking) into battery life prediction for EV use cases [81,82]. Additionally, vision transformer (ViT) models with transfer learning have been applied to SoH estimation by treating cycle data as

image-like inputs, achieving improved feature extraction and transferability across battery types [83,84]. Further enhancements include CEEMDAN-augmented transformer models for SoH prognostics and RUL prediction, allowing for the separation of long-term trends and short-term fluctuations [85]. These advances underscore the transformer architecture's flexibility in capturing complex battery degradation patterns from diverse data modalities and experimental conditions—all enhancing prognostic performance and generalization.

Further, Nakano & Tanaka implemented a transformer-based online SoH estimation model using real-world EV driving data [86]. This model processes raw sequences of voltage, current, SoC, and vehicle speed with a transformer encoder, achieving an MAE of 1.31% and RMSE of 2.08%, while highlighting through attention maps that the model naturally focuses on stationary driving periods as particularly informative for SoH prediction [86].

2.4.5. Physics Informed Machine Learning and Physics Informed Neural Networks

Physics-informed AI models—especially physics-informed neural networks (PINNs)—have been applied to SoH estimation for lithium-ion batteries to combine data-driven flexibility with electrochemical consistency. Purely data-driven methods (e.g., standard RNNs or LSTMs) can achieve high accuracy on large, representative datasets but may generalize poorly to new chemistries or operating conditions [87]. Conversely, pure physics models such as the pseudo-two-dimensional (P2D; Doyle–Fuller–Newman) model are interpretable but computationally intensive and require many internal parameters that are difficult to measure. PINNs address this trade-off by embedding governing equations—e.g., diffusion (Fick's law) and charge-/mass-conservation from the P2D framework, along with degradation sub-models such as solid-electrolyte interphase (SEI) growth—into the learning objective [88,89]. In practice, this is typically achieved by augmenting the data-fitting loss with physics-based penalty terms, leading to a composite loss function of the following form:

$$\left(L = L_{data} + \lambda L_{physics}\right)$$

where L_{data} enforces agreement with measured voltage, capacity, or SoH data, $L_{physics}$ penalizes violations of governing PDE/ODE constraints and boundary or initial conditions, and λ controls the balance between data fidelity and physical consistency.

Concretely, the loss augments the data-fit term with residuals of the PDE/ODE operators and boundary/initial conditions to penalize violations of known electrochemical relations, thereby regularizing the model toward physically consistent solutions. This hybrid formulation is particularly beneficial in data-scarce regimes and can improve robustness and interpretability in SoH estimation [54,89–92].

PINN performance depends on appropriate nondimensionalization/scaling and on balancing the data and physics residual terms in the loss; identifiability of parameters may require informative priors or experiments. Terminology and symbols should be kept consistent (SoH; x_t, h_t, C_t; P2D), and not all degradation phenomena are strictly PDE-governed—some are better represented by ODE or algebraic sub-models—so the physics constraints should match the chosen mechanistic assumptions.

3. Experiments

3.1. Overall Workflow

The entire workflow for AI-based SoH prediction for batteries consists of four main stages as shown in Figure 8, namely:

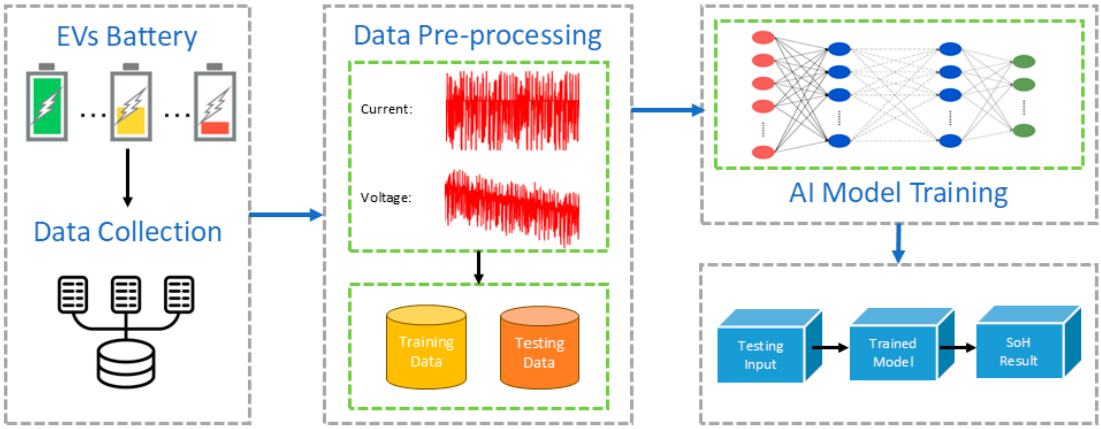

Figure 8. Workflow of AI-driven state of health (SoH) prediction for Li-ion batteries.

Step 1: Data Collection. Raw data are acquired from batteries during charge–discharge cycles and, commonly, the captured measurements include current, voltage, temperature, and cycle count. The BMS logs data continuously during use or data can also be extracted from public datasets e.g., NASA, CALCE, and Oxford.

Step 2: Data Pre-processing. The downloaded raw signals are typically noisy and inconsistent and require pre-processing. Pre-processing entails stage, filtering, normalization, and segmentation of the current–voltage profiles into segments, which represent a typical segment of charging current profile (i.e., constant current charging segment). If available, multimodal sensor fusion such as temperature, incremental capacity/differential voltage (i.e., dQ/dV or dV/dQ) and/or impedance spectroscopy measurements can enrich the data and allow for greater robustness in the prediction of battery SoH [93–98]. In practice, measurements via sensors are noisy, intermittent, inconsistent, and often have missing data. In addition, the single unique real-world use case, battery chemistry, and operational condition of datasets can introduce real-world biases [19,26,99]. Once processed, the data are generated by splitting into training and testing datasets so that supervised and unbiased models can be developed.

Step 3: AI Model Training and Prediction. Once the data have been pre-processed, they are loaded into AI models as they attempt to learn the nonlinear mapping between the input features and the indicators of battery health. If used, models may be pretrained on limited data sets to speed up the training process; pre-training also allows training on batteries where some of the history of the battery is not available (a strategy often referred to as "pretraining on source, fine-tuning on target") [100–106]. There are previously mentioned AI architectures such as feed-forward neural networks, LSTM, CNN, and transformer-based models which capture temporal dynamics and complex modes of degradation [107]. After training the AI models, the models are evaluated using unseen input data, to predict SoH indicators.

Step 4: Evaluation. The predicted SoH values are evaluated against the ground truth (real SoH values) using evaluation metrics such as MAE, RMSE and/or the coefficient of determination (R^2). Evaluation metrics should quantify accuracy and robustness, thus ensuring that the developed models should be applicable in battery management systems. The structured workflow involving data collection, data pre-processing, AI model training, and evaluation provide a reproducible and scalable pipeline of SoH prediction using different datasets and applications.

3.2. Benchmark Datasets

Data are crucial for AI models. There is a famous saying in AI that describes the AI training process as "Garbage in and garbage out." This suggests that, when an AI model

is trained with excellent data, that excellent results will obtain, and vice versa. Therefore, for EV battery SoH prediction, commonly used datasets come primarily from laboratory-measured battery aging experiments or public battery databases. Most research work is based on public battery databases. Currently, the most commonly used battery datasets are the NASA Battery Dataset [32], the CALCE Battery Dataset [33], and the Oxford Battery Degradation Dataset [14,34], as summarized in Table 1.

Table 1. Comparison of commonly used public datasets for battery SoH prediction.

Dataset	Data Scale	Measured Signals	Advantages	Limitations
CALCE battery dataset	Multiple commercial Li-ion cell types (e.g., $LiCoO_2$ and $LiMn_2O_4$) Dozens of cells >1000 cycles in some cases under different rates and temperatures	Voltage Current Capacity Temperature Internal resistance (partial)	Diverse cycling protocols with wide variations in C rates and temperatures Provides additional degradation indicators (e.g., resistance)	Data format varies, requiring preprocessing
NASA battery dataset	4 Li-ion 18,650 cells ~100–200 cycles per cell under different cycling conditions	Voltage Current Capacity Temperature (partial)	Benchmark for SoH/RUL prediction One of the earliest and most widely used public datasets	Limited number of cells (only 4) Low sampling frequency Relatively simple operating conditions
Oxford battery degradation dataset	Dozens of commercial Li-ion cells Systematic lifetime cycling until cell failure	Voltage–capacity curves Current Capacity degradation trajectory	High-quality, low-noise data Includes detailed d_Q/d_V analysis	Limited number of cells Operating conditions relatively fixed (laboratory-controlled)

Having a number of datasets representing different battery chemistry, aging mechanisms, environment, and operational loads can lead to opportunities in transfer learning, potentially leading to gains in effort required to train a model between similar cases, and possibly lead to efficient, lightweight, and edge optimized models [108–113].

- **NASA Battery Dataset:**

The NASA battery dataset is one of the most commonly utilized datasets in battery prognostics literature, from the Prognostics Center of Excellence, NASA Ames. It provides cycling data of commercially available Li-ion cells, normally using $LiCoO_2$ chemistry, cycled under constant current charge–discharge protocols to end-of-life (which is approximately 70–80% of rated capacity) [32]. The dataset contains cycle number, capacity, voltage, current, surface temperature, and has a relatively high sampling frequency to allow detailed tracking of degradation trajectories. Several cells were tested, including commonly used ones like B0005, B0006, B0007, and B0018, cycled under the same operating conditions, making it great for algorithm benchmarking and reproducibility studies. Because of the standardization and ease of public accessibility, the NASA dataset (or parts of it) has frequently been regarded as the baseline for SoH prediction research despite its limited diversity of operating conditions limiting its ability to represent more complex battery usage in the real world.

- **CALCE Dataset:**

The CALCE dataset, which was created by the Center for Advanced Life Cycle Engineering at the University of Maryland, goes a step further, with a more diverse and heterogeneous set of degradation trajectories. The CALCE cells, which are usually $LiCoO_2$- or $LiMn_2O_4$-based chemistries, were cycled with several different experimental protocols, using different discharge rates, temperatures, and depths of discharge. This approach introduces many degradation pathways so the dataset can capture how different operating and environmental stresses accelerated capacity fade and growth of resistance. As the CALCE dataset embodies a huge swath of data for different operating regimes, it is ideal for evaluating the robustness and transferability of an AI model in a way that cannot be achieved with a static protocol. The variability also makes it attractive for research in domain adaptation and transfer learning. However, the heterogeneity, and potential complexity, of the CALCE data necessitates even more elaborate preprocessing for consistent training of models [33].

- **Oxford Battery Degradation Dataset:**

In contrast, the Oxford dataset provided by the University of Oxford offers a different viewpoint as the focus is on lithium iron phosphate ($LiFePO_4$/graphite) cells cycled at a very wide range of current rates, including fast charging. The major highlight is the high-resolution measurements, which include many long-cycling, discharge, and charge measurements of voltage, current, and capacity on the same cells. The lifespan of the cells in the dataset varies based on the charging and discharging protocol, with durations as low as 150 charge–discharge cycles or as high as over 2300, thereby giving a large perspective of the extent of degradation with these varied charging and discharging regimes. The fine-grained measurements allow for precise feature extraction, including incremental capacity curves and small shifts in the plateaus of the voltage profiles, which is particularly valuable for training deep learning models that require nuanced signal patterns. While the Oxford Dataset is not based on multiple chemistries, and only based on $LiFePO_4$, which itself is just one of many commonly used cathodes in electric vehicles, it is becoming more relevant when considering the growth in commercial applications of $LiFePO_4$ batteries, particularly where long cycle life and safety are a priority [34].

Leveraging the combined NASA, CALCE, and Oxford datasets [32–34], provides a rigorous benchmarking framework for AI-based SoH prediction. The NASA dataset acts as the classical benchmark dataset, as it has become an increasingly cited reference throughout the literature based on reproducibility and accessibility; however, it is limited in scope (a relatively low number of cycling examples) and therefore not representative of real-world applications due to lack of cycling diversity. The CALCE dataset provides a greater scope of battery operating conditions (C rates, operating or depth of discharge) thus it serves as a more representative example, closer to a real-world EV, and is appropriate for assessing model robustness and transferability. The Oxford dataset, although limited specifically to the $LiFePO_4$ chemistry, has provided clean, high-resolution measurements for many different cycling protocols, and is particularly potent for advanced machine learning techniques which are best suited to fine features.

In Figure 9 the authors provide a radar chart depicting the three datasets according to three comparisons—scale, signal richness, and intended application—showing that NASA represents a degree of standardization as a baseline measure; however, it still suffers from both a scale and signal richness comparison. CALCE represents the spectrum of application and realism and Oxford offers an additional degree of protection for both data cleanliness and resolution, providing sufficient detail for deeper analysis of the more subtle degradation behaviors. When considered together, these datasets provide a collective product and support a balanced framework for assessing AI models across ironing chemistries, operational conditions, and applications.

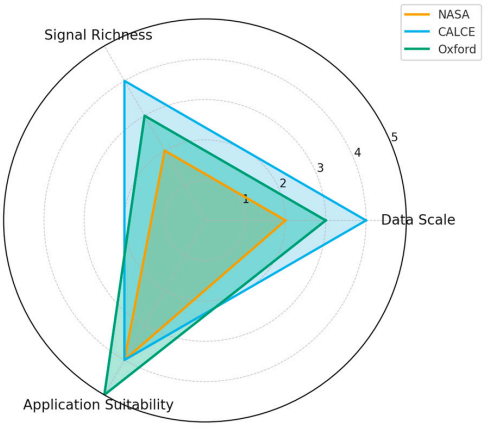

Figure 9. Qualitative, conceptual comparison of commonly used SoH prediction datasets based on dataset scale, signal richness, and intended application.

- **Other Datasets:**

Beyond these, several emerging datasets offer broader data diversity and real-world applicability. The BatteryLife dataset aggregates 16 datasets across multiple chemistries, formats, and test conditions, providing extensive support for benchmarking battery life prediction models [114]. The PulseBat dataset focuses on second-life Li-ion cells, featuring pulse-testing data for rapid diagnostics under varied SoH and temperature conditions [115]. Additionally, a large-scale run-to-failure dataset of 55 Li-ion batteries offers a unified data preprocessing pipeline, enabling comparative and scalable SoH modeling [116]. These additional datasets enrich the field with real-world variability, capacity data spans, and diagnostic depth.

3.3. Evaluation Metrics

To quantitatively assess the performance of the AI-based SoH estimation models, many discriminatory regression measures are used, mostly in a complementary manner, in assessing accuracy, robustness, and usability. The mean absolute error (MAE) is adopted frequently in practice and measures the average magnitude of the prediction error, as follows:

$$MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

where $\hat{y}_i$ and y_i denote the predicted and actual SoH values, and n is the number of observations. MAE provides an interpretable measure of deviation that is less sensitive to outliers and is therefore better suited for practical diagnostic applications.

RMSE provides another vantage point on the problem, and also assesses larger deviations more severely:

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

In contrast to MAE, RMSE emphasizes larger prediction errors. This is important in battery prognostics, where the occasional large deviation causes serious errors in safety, or maintenance scheduling.

The coefficient of determination (R^2) measures the proportion of variance in the true SoH values that is explained by the model:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\hat{y}_i - \overline{y_i})^2}\right]$$

where $\overline{y}$ is the mean of the observed values. R^2 values that are closer to 1 indicate strong explanatory power. Lower R^2 values would indicate limited ability to explain the underlying degradation trends. This measurement is especially useful for model comparison across datasets with different distributions.

Along with these statistical measures, relative error within thresholds is often reported in order to assess practical applicability. For example, with a tolerable deviation of $\pm 2\%$ the proportion of predictions that fall within the specified band can be defined as follows:

$$Accuracy \pm 2\% = \left(\frac{1}{n}\right)\sum_{i=1}^{n} 1(|\hat{y}_i - y_i| \leq 0.02)$$

where $1(\cdot)$ is the indicator function. This threshold-based metric directly supports the precision requirements of BMSs, as even small deviations on the SoH prediction can affect safety margins, warranties, and energy management decisions. In conclusion, the combined evaluation of MAE, RMSE, R^2, and relative accuracy thresholds provide a multi homogenous evaluation framework that balances statistical error measurement and practical deployment factors to ensure an encompassing approach to the assessment of AI models in SoH prediction [117–119]. Although these pointwise metrics are used extensively, they possess limitations in determining the state of health and remaining useful life of batteries. For example, low average errors (e.g., MAE or RMSE) can obscure significant systematic errors or accumulation of underestimation that occurs during the advanced stages of battery degradation, as there is an increased associated operational and safety risk. Additionally, in order to evaluate the complete reliability and applicability of predictive battery modelling methods and their associated technologies for real-world use, additional analyses are commonly performed on the accuracy of the predicted results and how accurately those predictions correlate with the operator's expectations based on previous experience with such technologies.

4. Comparison and Evaluation of AI Prediction Methods

Traditional machine learning, MLPs, RNNs, LSTMs, hybrids, and transformers, each exhibit unique strengths and limitations in accuracy, computational burden, data requirements, and interpretability.

Instead, this paper adopts a literature-based comparative analysis approach, where representative AI models are compared based on their reported results on widely used public datasets (e.g., NASA, CALCE, and Oxford), as documented in the original publications. The purpose of this comparison is to highlight relative trends, architectural characteristics, strengths, and limitations of different model families, rather than to provide a unified experimental benchmark.

4.1. Traditional Machine Learning Methods

Traditional ML approaches, such as support vector regression (SVR), random forest (RF), and Gaussian process regression (GPR), serve as lightweight baselines. RF, often paired with CNNs through feature fusion, delivers reliable accuracy with interpretability and computational efficiency—especially using incremental capacity indicators. The limitations of RF and SVR lie in their limited ability to model temporal dependencies compared with deep architectures [120,121].

4.2. Multilayer Perceptron

MLP networks remain favorable due to their simplicity and speed. Enhanced MLPs integrating PCA, optimized via heuristics, such as GWO and particle swarm optimization (PSO), or combined with attention modules, have improved robustness and minimized

overfitting, achieving < 1.5% RMSE in some studies. Nonetheless, MLPs still fall short of modeling the temporal dependencies critical for cycle-based SoH forecasts.

4.3. Recurrent Neural Networks (RNNs) and Variants

Independent RNNs (IndRNNs), GRUs, and parallel RNNs retain relevance for SoH prediction, offering temporal modeling with efficiency. However, their limitations in capturing long-range dependencies position LSTMs as a more potent alternative, especially when engineered with attention or feature fusion.

4.4. Long Short-Term Memory (LSTM)

LSTM-based methods augmented with attention, transfer learning, or hybrid KAN-LSTM models are notably effective for modeling long-range battery degradation patterns. Their strong performance (e.g., <2% relative error) is counterbalanced by higher computational cost and memory demand, which may hamper embedded BMS deployment.

4.5. Hybrid Deep Learning Approaches

Hybrid CNN–LSTM–attention models, particularly ones optimized with FVIM, deliver remarkable accuracy (MAE $\approx$ 0.99%, RMSE $\approx$ 1.33%) by combining spatial feature extraction, temporal modeling, and optimization—though they introduce complexity and resource demands.

4.6. Transformer-Based Models

The transformer family—spanning CyFormer, Transformer–GRU, Transformer–LSTM, and real-world driving data transformers—offers excellent data efficiency, interpretability (via attention), and accurate long-term insight without recurrence. However, these benefits come with increased data, parameter, and compute requirements.

4.7. Comparative Evaluation

In summary, traditional machine learning methods like random forest and SVR offer computational efficiency and interpretability, making them practical baselines—though they lack the temporal modeling power of deep learning architectures. MLP-based approaches improve on this through richer feature integration and optimization techniques but still fall short in modeling sequence dependencies. RNNs could provide lightweight temporal modeling capabilities but may have poor performance when handling long sequences because of the vanishing gradient problem [24]. By contrast, LSTMs, particularly with attention enhancements and hybrid strategies, offer strong long-range sequence modeling at the cost of higher computational and memory demands. Hybrid CNN–LSTM–attention frameworks push predictive accuracy to impressive levels while significantly increasing model complexity. Transformer-based models, such as CyFormer and Transformer–GRU/LSTM hybrids, combine high accuracy, data efficiency, and interpretability through attention mechanisms—but often remain resource-intensive and pose challenges for real-time or embedded deployment. While techniques, such as feature reconstruction using CEEMDAN for preprocessing, are capable of improving the accuracy of prediction significantly, the added computational costs can limit the use of these methods within real-time battery management systems. The following table (Table 2) provides a structured summary of these methods, comparing their architectural characteristics, strengths, limitations, and empirical performance outcomes. Table 3 summarizes representative and well-performing AI networks. The purpose of this table is to highlight relative trends, strengths, and limitations based on the results reported in the original papers of these networks, rather than to provide a controlled experimental comparison.

Table 2. Model strengths and limitations.

Model Type	Strengths	Limitations
Traditional ML	Efficient, interpretable, feature importance insights	Limited in automatic temporal dependency learning, static representations
MLP	Fast, simple, enhanced via feature optimization strategies	Limited temporal awareness, potential overfitting
RNN/GRU/IndRNN	Good temporal modeling, lightweight	Weak at long-term dependencies, parameter sensitivity
LSTM + attention	Strong sequence modeling, trend capture	High computational burden, less edge-friendly
Hybrid CNN–LSTM–Attention	High accuracy via spatial–temporal fusion	Complex design, high tuning requirement
Transformer variants	Data efficient, interpretable, modeling long dependencies	Heavy computational burden, less edge friendly

Table 3. Comparison of AI-based prediction methods for Li-ion battery SoH estimation.

Model Type	Representative Studies	Architecture Highlights	Dataset	Performance
Traditional ML	Yang et al. [44], Wang et al. [45], Gotz et al. [46], Rout et al. [47]	CNN-RF fusion, IC curve features, second-life battery grouping, SVR and GPR variants	NASA, CALCE, custom 2nd-life	Improved robustness; effective with partial discharge; fast and interpretable
MLP	Lai et al. [51], Li et al. [52], Lei et al. [53], Bao et al. [14], Wang et al. [54]	PCA + optimization (GWO), patch-based MSPMLP, physics-informed MLPs, interpretable visual boundaries	NASA, CALCE	RMSE < 1.5%; MAE improved by ~42%; interpretable and robust
RNN/GRU/ IndRNN	Venugopal et al. [55], Teixeira et al. [56], Chen et al. [57], Qaadan et al. [58], Wen et al. [59], He et al. [60]	GRU, IndRNN, BiGRU with search algorithms, MM-GRU for multi-input tracking	NASA, CALCE, Oxford	Adaptable to variable loads; real-time capable; moderately lightweight
LSTM & Hybrid Variants	Xu et al. [63], Yao et al. [64], Zhang et al. [66], Liu et al. [68], Tasnim et al. [69], Xiao et al. [70], Zhao et al. [72]	LSTM + attention, KAN–LSTM, CNN–LSTM–attention-FVIM, dual-stream BiLSTM	NASA, CALCE, Oxford	MAE ≈ 0.99%, RMSE ≈ 1.33%; robust to regeneration; high temporal fidelity
Transformer Models (Survey)	Guirguis & Ahmed [23]	General transformer architectures for SoH/SoC; survey-based	Multiple public datasets	Superior to traditional ML; interpretable attention maps
CyFormer (Transformer)	Nie [77]	Cyclic attention across inter/intra cycles	Custom cyclic degradation	MAE = 0.75% with 10% tuning data
Transformer–GRU Fusion	Chen et al. [24]	CEEMDAN + filtering + cross-attention + GRU	Oxford, ICC data	RMSE reduced by >60% vs baseline
Transformer–LSTM Fusion	Cai & Liu [25]	Transformer encoder + LSTM decoder + SoC/voltage/ frequency fusion	124 fast-charging $LiFePO_4$ cells	Robust to protocol variability; high generalization
Real World Transformer	Nakano & Tanaka [86]	Transformer on raw EV driving signals (voltage, speed, SoC)	In-vehicle EV data	MAE = 1.31%, RMSE = 2.08%; attention aligned with driving conditions

5. Conclusions

This paper reviewed recent advances in the application of artificial intelligence (AI) to battery state of health (SoH) estimation and prognostics, particularly remaining useful life (RUL) prediction. While significant progress has been made using machine learning and

deep learning techniques, several key barriers continue to limit the practical deployment of AI-based methods in battery management systems (BMSs).

First, data quality and availability remain fundamental challenges. High-quality, representative datasets are essential for reliable model training and evaluation, yet existing datasets often suffer from limited coverage, inconsistent operating conditions, and incomplete life-cycle information. These limitations constrain both prediction accuracy and model generalizability.

Second, the lack of interpretability poses a major obstacle to adoption. Many high-performing models, such as LSTMs and transformer-based architectures, function as black boxes. For safety-critical systems like electric vehicles, practical deployment requires interpretable outputs that support regulatory compliance, fault diagnosis, and human trust. Although the importance of explainable AI (XAI) is widely recognized, systematic and battery-specific interpretability frameworks for SoH and RUL applications remain underdeveloped.

Third, transfer learning challenges persist. Models trained on specific battery chemistries, usage profiles, or testing protocols often exhibit degraded performance when applied to different operating conditions or cell types. Robust cross-domain adaptation remains an open research problem.

Based on this review, four actionable research directions are identified to address these challenges and advance deployable AI-based SoH estimation:

1. Hybrid Models and Physics Integration: Hybrid approaches that incorporate physics-informed constraints or electrochemical knowledge into data-driven models can improve reliability, interpretability, and transferability. By bridging purely data-driven learning with physical understanding, such models offer a promising pathway toward more robust SoH prediction.
2. Self-Supervised and Unsupervised Learning: Given the scarcity of labeled battery degradation data, self-supervised and unsupervised learning methods—such as contrastive learning, predictive pretext tasks, and phase-space modeling—can enable effective representation learning with reduced reliance on labeled data. These approaches can significantly lower annotation costs and support scalable model development.
3. Lightweight and Edge-Optimized Models: Battery management systems typically operate on resource-constrained embedded platforms. Consequently, lightweight architectures employing techniques such as model pruning, quantization, knowledge distillation, and TinyML are essential. While such methods are well established in embedded AI, their systematic application to battery SoH models—particularly recurrent and attention-based architectures—remains limited and warrants further investigation.
4. Multimodal Sensor Fusion: Beyond voltage and current, batteries generate additional informative signals, including temperature, pressure, acoustic emissions, and impedance measurements. Multimodal sensor fusion, combined with attention-based or cross-modal learning frameworks, offers the potential to enhance prediction robustness, fault sensitivity, and overall system reliability.

Pursuing these research directions will help advance AI-driven SoH models toward solutions that are not only more accurate, but also more interpretable, transferable, and deployable across battery chemistries, operating conditions, and real-world applications.

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