

Review

Machine Learning Techniques for Battery State of Health Prediction: A Comparative Review

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Abstract

Accurate estimation of the state of health (SOH) of lithium-ion batteries is essential for the safe and efficient operation of electric vehicles (EVs). Conventional approaches, including Coulomb counting, electrochemical impedance spectroscopy, and equivalent circuit models, provide useful insights but face practical limitations such as error accumulation, high equipment requirements, and limited applicability across different conditions. These challenges have encouraged the use of machine learning (ML) methods, which can model nonlinear relationships and temporal degradation patterns directly from cycling data. This paper reviews four machine learning algorithms that are widely applied in SOH estimation: support vector regression (SVR), random forest (RF), convolutional neural networks (CNNs), and long short-term memory networks (LSTMs). Their methodologies, advantages, limitations, and recent extensions are discussed with reference to the existing literature. To complement the review, MATLAB-based simulations were carried out using the NASA Prognostics Center of Excellence (PCoE) dataset. Training was performed on three cells (B0006, B0007, B0018), and testing was conducted on an unseen cell (B0005) to evaluate cross-battery generalisation. The results show that the LSTM model achieved the highest accuracy (RMSE = 0.0146, MAE = 0.0118, $R^2 = 0.980$), followed by CNN and RF, both of which provided acceptable accuracy with errors below 2% SOH. SVR performed less effectively (RMSE = 0.0457, MAPE = 4.80%), reflecting its difficulty in capturing sequential dependencies. These outcomes are consistent with findings in the literature, indicating that deep learning models are better suited for modelling long-term battery degradation, while ensemble approaches such as RF remain competitive when supported by carefully engineered features. This review also identifies ongoing and future research directions, including the use of optimisation algorithms for hyperparameter tuning, transfer learning for adaptation across battery chemistries, and explainable AI to improve interpretability. Overall, LSTM and hybrid models that combine complementary methods (e.g., CNN-LSTM) show strong potential for deployment in battery management systems, where reliable SOH prediction is important for safety, cost reduction, and extending battery lifetime.

Keywords: State of Health (SOH); machine learning (ML); electric vehicles (EVs); battery health; long-short-term-memory (LSTM); convolution neural network (CNN); Random Forest (RF); Support Vector Regression (SVR)



Academic Editor: Michael Fowler

Received: 8 September 2025

Revised: 17 October 2025

Accepted: 25 October 2025

Published: 28 October 2025

Citation: Mbagaya, L.; Reddy, K.; Botes, A. Machine Learning Techniques for Battery State of Health Prediction: A Comparative Review. *World Electr. Veh. J.* **2025**, *16*, 594. <https://doi.org/10.3390/wevj16110594>

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1. Introduction

The growing dependence on batteries for electric vehicles—with global electric vehicle (EV) sales projected to reach 30 million annually by 2030 [1]—has made it crucial to precisely measure and forecast battery health. The state of health (SOH) is usually defined as the ratio (percentage) of the battery's current available capacity to the initial rated capacity [2]. The precise measurement of SOH is vital to achieving maximum battery efficiency and maximising the life and safety of all its applications.

Multiple factors influence battery SOH, including temperature, charge/discharge cycles, depth of discharge (DoD), and operating conditions [3]. High temperatures within a battery accelerate chemical reactions such as electrolyte decomposition and electrode material degradation, which results in capacity reduction. Battery cells are subjected to mechanical stress along with loss of active material as a result of regular charging and discharging operations, especially at high discharge depths. Furthermore, battery degradation worsens when they are exposed to overcharging and high current rates and when stored under improper conditions [4]. These complex interrelated factors make the prediction of SOH challenging as they vary between battery chemistries and use cases. Therefore, accurate SOH prediction is critical to ensure safety, optimise performance, and reduce costs.

Currently, the SOH of the battery is estimated on the basis of direct measurements and physical models. Common methods for direct measurement include Coulomb counting [5], which tracks the flow of charge to estimate the reduction in capacity, and electrochemical impedance spectroscopy (EIS) [6], which analyses changes in impedance. Physics-based approaches include equivalent circuit models (ECMs) [7] and empirical models, which simulate battery behaviour or are based on laboratory test data. These methods rely on measurable parameters such as voltage, current, temperature, and impedance to estimate the SOH. Despite their widespread use, these traditional SOH estimation methods have significant limitations. Coulomb counting is prone to cumulative errors over time, especially under dynamic operating conditions. EIS requires specialised equipment and controlled environments, making it impractical for real-time applications, whereas ECM and empirical models often simplify complex degradation mechanisms, leading to reduced precision for batteries outside of the tested conditions [7]. Additionally, these methods struggle to account for the nonlinear and interdependent effects of ageing factors, resulting in poor generalisability across different battery types and usage scenarios. For these reasons, there exists a need for more reliable means of battery SOH estimation. This brings about the utilisation of machine learning for the purpose of battery SOH prediction.

Machine learning, a subfield of artificial intelligence, involves algorithms that learn patterns from data to make predictions or decisions without being explicitly programmed. Machine learning (ML) algorithms, such as neural networks [8], support vector machines [9], and decision trees [10], can learn intricate patterns from large datasets comprising voltage, current, temperature, and cycle data. Therefore, they are able to model battery degradation more accurately and in a scalable data-driven manner across diverse operational conditions. For example, Xu et al. [11] used a hybrid machine learning model that uses both convolution neural networks (CNNs) and a long short-term memory (LSTM) algorithm to estimate the state of health of lithium-ion batteries. Validation of the approach was performed on NASA and Oxford battery datasets and the results showed improved accuracy and robustness, with RMSE below 0.004. Such results underscore the potential of ML-based models to overcome the limitations of traditional methods by capturing both spatial and temporal dependencies in battery performance data.

Despite their promise, ML models are not without limitations. Challenges include data dependency, model interpretability, and the need for large high-quality training

datasets [12]. Nonetheless, ML provides a powerful framework for generalising across battery types and operational conditions, which are areas where traditional methods fall short. This article provides a review of four widely used ML techniques in SOH estimation, critically evaluating their merits, demerits, and advancement. Additionally, a simulation of the four techniques is carried out on a sample dataset to analyse and compare the performance of these ML algorithms.

The contributions of this paper are as follows:

- i. A comprehensive literature review of four widely used ML algorithms in SOH prediction, namely support vector regression (SVR), long short-term memory (LSTM), convolution neural networks (CNNs), and random forest (RF), including relevant mathematical formulations.
- ii. An evaluation of the strengths, limitations, and recent advancements of each algorithm.
- iii. A MATLAB R2025a-based simulation to assess and compare the performance of the four selected ML models in SOH prediction.

2. Machine Learning Algorithms in State of Health Prediction

Several recent studies have applied ML methods to batteries in EV contexts. This section explores the application of four commonly used ML algorithms, namely support vector regression (SVR), convolutional neural network (CNN), long short-term memory (LSTM), and random forest (RF). It examines their methodologies, strengths, and challenges, highlighting their potential to improve battery health prediction.

2.1. Support Vector Regression

SVR is a supervised learning algorithm designed for regression tasks. SVR differs from standard linear regression in that it only calculates losses when prediction errors exceed a defined tolerance ε while optimising model performance through the maximum interval bandwidth and minimum total loss [13]. The regression problem requires finding an optimal hyperplane that positions all sample points at their closest distance from the hyperplane, as shown in Figure 1 [14].

For a linear hard-spaced SVR, the optimisation objective is as follows:

$$\frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*), \quad (1)$$

which are subject to the following constraints:

$$\begin{cases} y_i - (w, x_i) - b \leq \varepsilon + \xi_i \\ (w, x_i) + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0. \end{cases} \quad (2)$$

The constraints ensure that the predictions, given by

$$f(x_i) = (w, x_i) + b, \quad (3)$$

lie within an ε -tube around the true targets y_i while allowing some flexibility through the slack variables. The parameter ε allows the predicted value to have no loss within the range of ε and reduces the impact of noise.

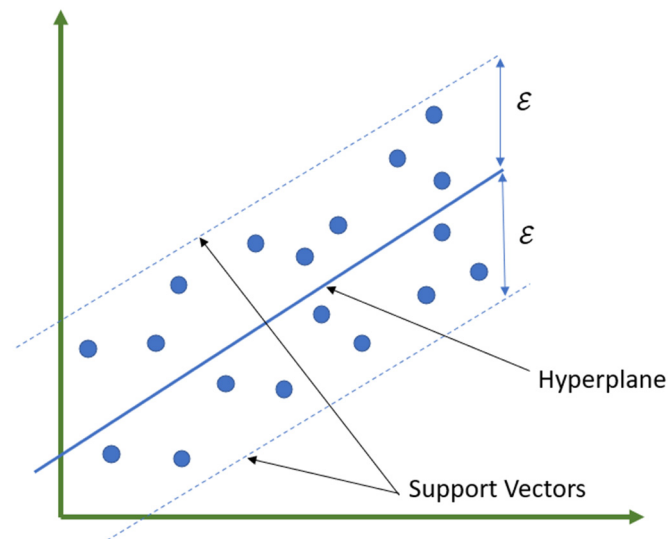


Figure 1. Illustration of 1D linear SVR, showing the hyperplane, support vectors, and tolerance ε , adapted from ref. [14].

To solve this constrained optimisation, SVR is typically formulated in its dual form using Lagrange multipliers. The dual problem involves optimising the Lagrange multipliers α_i , α_i^* , leading to the regression function:

$$f(x) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) K(x_i, x) + b \quad (4)$$

where w is the weight vector, C is the regularisation parameter, ε is the tube width, ξ_i and ξ_i^* are slack variables, α_i and α_i^* are Lagrange multipliers, and $K(x_i, x)$ is the kernel function. The regularisation parameter, C , controls the trade-off between model complexity and error tolerance. The greater the C , the heavier the penalty for errors that exceed the range of ε .

Kernels enable SVR to handle nonlinear relationships by implicitly mapping data into higher-dimensional spaces. Common kernels include linear, polynomial, sigmoid, and radial basis functions and are given in Table 1.

Table 1. Common kernels and their equations.

Linear Kernel	$K(x_i, x) = (x_i, x)$
Polynomial Kernel	$K(x_i, x) = (\gamma(x_i, x) + r)^d$
Radial Basis Function Kernel (Gaussian Kernel)	$K(x_i, x) = \exp(-\gamma \ x_i - x\ ^2)$
Sigmoid Kernel	$K(x_i, x) = \tanh(\gamma(x_i, x) + r)$

where γ is the scaling factor, r is the bias, and d is the degree of polynomial. Proper selection and tuning of kernel parameters are critical to model performance and generalisation.

One of the key merits of SVR is its robustness to outliers and its high prediction accuracy, which is particularly valuable in SOH prediction, where battery data often exhibit noise due to varying operating conditions. Zhao et al. [15] employed SVR to estimate SOH based on capacity fade data from lithium-ion batteries, using features derived from charge/discharge cycles. Their model achieved a mean absolute error (MAE) of less than 2% across multiple datasets, leveraging SVR's epsilon-insensitive loss function to mitigate the impact of outliers on voltage and capacity measurements. This robustness ensured reliable predictions despite irregularities in battery degradation patterns. Another study [16] reported mean R^2 values of up to 0.962 for test sets using full discharge data. For partial discharge windows, the model maintained strong performance across most

voltage ranges, except for high-voltage intervals. The study highlights the robustness, computational efficiency, and applicability of SVRs to real-world scenarios, particularly with partial data, although it notes limitations with outlier batteries exhibiting unique degradation patterns.

The flexibility of SVRs in modelling nonlinear relationships through kernel functions is another significant advantage. This is evident in the work by Chen et al. in which they employed a radial basis function kernel in an SVR-based model using partial charge voltage and current data to estimate SOH. The model achieved a mean squared error (MSE) < 0.00052 and a mean absolute relative error (MARE) $< 0.93\%$ on two test cells. In [17], Feng et al. constructed a hybrid kernel function of the polynomial kernel function and radial basis function, compensating for the shortcomings of single kernel functions. This improved the model's generalisation ability and learning ability and enhanced the nonlinear modelling ability of the model, effectively avoiding overfitting the training set.

Recent researchers have used optimisation algorithms to tune hyperparameters such as C and ϵ to improve accuracy and SVR's model stability. In [18], the authors employed the particle swarm optimisation (PSO) algorithm to estimate the SVR kernel parameter. The improved PSO–SVR model showed great robustness when the training data contained noise and measurement outliers. Recent work by Vedhanayaki and Indragandhi [19] introduced a Bayesian optimised support vector regression (BO-SVR) framework with a Gaussian kernel for SOH estimation. Their study employed the equivalent charging voltage difference interval (ECVDI) and equivalent discharging voltage difference interval (EDVDI) as inputs, achieving a remarkably low RMSE of 0.0082, outperforming both standard kernel SVR and Gaussian process regression models. Xia et al. [20] proposed an impedance-based SOH estimation framework that combines feature selection and an improved support vector regression model. The sine sparrow search algorithm (Sine-SSA) was applied for hyperparameter tuning of SVR. Using a large commercial EIS dataset across multiple temperatures, the model achieved a maximum error of 2.58%, outperforming LSTM and conventional SVRs.

The grey wolf optimisation (GWO) algorithm, which features a basic structure, minimal adjustable parameters, and straightforward implementation, optimised both the kernel and penalty parameters of kernel SVM in [21]. This implementation led to a longer runtime as the data increased compared with a non-optimal KSVM. Other algorithms that have been used include the ant lion optimisation algorithm [22], ant colony optimisation [23], and dung beetle optimisation [24].

Despite the improvements in accuracy and model stability with the use of optimisation algorithms, SVR models may become computationally expensive for large datasets and require careful feature selection to avoid overfitting. The data dependency of SVRs also limits their applicability to emerging chemistries such as sodium-ion or solid-state batteries, a key gap in the scope of the research [25].

2.2. Long Short-Term Memory

Long short-term memory (LSTM) networks are a specialised type of recurrent neural network (RNN) designed to model and predict sequential data with long-term dependencies, making them ideal for time series tasks. Unlike traditional RNNs, which often suffer from vanishing or exploding gradients, LSTMs introduce a memory cell and three gates (input, forget, and output) to selectively remember or forget information over extended time periods [26].

Figure 2 shows the core structure of an LSTM [27]. The architecture includes:

- A memory cell that maintains a cell state C_t , which carries information across time steps, enabling long-term memory.

- Gates that control the flow of information. The gates are as follows:
 - Forget gate: Decides what to discard from the previous cell state.
 - Input gate: Determines what new information to store.
 - Output gate: Selects what to output at the current time step.
- Each gate uses sigmoid (σ) and tanh activations to regulate information.

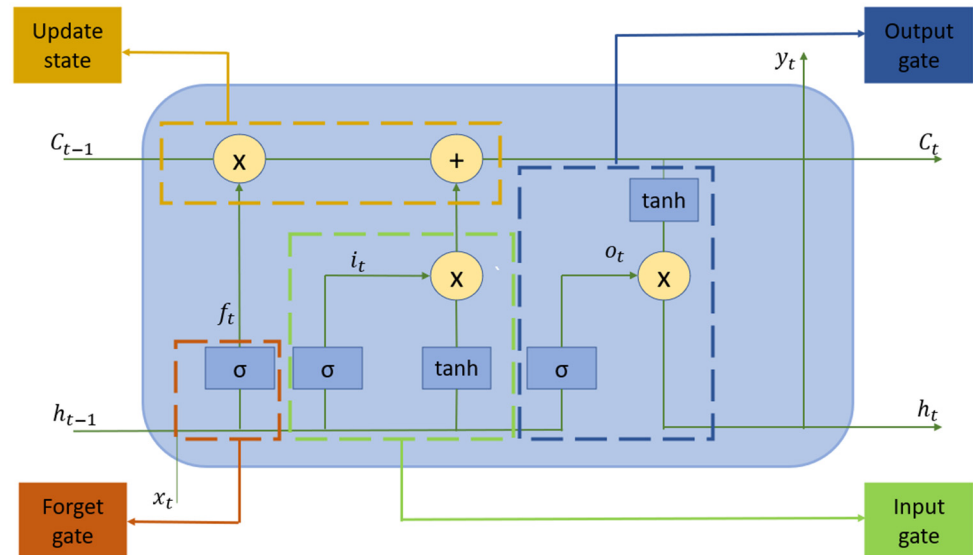


Figure 2. General architecture of an LSTM unit, showing memory cell and gates, adapted from ref. [27].

The forget gate is given by the following equation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (5)$$

where $f_t \in [0, 1]$ decides what to forget from C_{t-1} , W_f is the weight matrix of the forget gate, b_f is the bias term of the forget gate, and σ is the sigmoid activation function

The input gate consists of two stages. The first stage, the sigmoid layer, determines which value to update, and, in the second part, a tanh layer determines which value should be added to the state. The output of the first part is:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \quad (6)$$

where W_i is the weight matrix of the input gate, h_{t-1} is the output value at time $t-1$, x_t is the input at time t , b_i is the bias term of the input gate, and σ is the sigmoid activation function.

The output of the second part is given by:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (7)$$

where i_t selects new information, tanh is the activation function, $\tilde{C}_t$ is the candidate cell state, W_C is the weight matrix of the output gate, h_{t-1} is the output value at time $t-1$, x_t is the input at time t , and b_C is the bias term of the output gate.

The cell state is then updated by:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t. \quad (8)$$

The output gate has a sigmoid layer, which determines what information reaches the output. It is given by the following equation:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \quad (9)$$

where W_o is the weight matrix of the output gate, h_{t-1} is the output value at time $t - 1$, x_t is the input at time t , b_o is the bias term of the output gate, and σ is the sigmoid activation function. The output is given by:

$$h_t = o_t \cdot \tanh(C_t) \quad (10)$$

where h_t is the output at time t , o_t is the output value of the output gate at time t , and C_t is the long-term state of the unit at time t .

Several recent studies have explored LSTM-based methods for SOH prediction, addressing challenges such as capacity regeneration, hyperparameter optimisation, and data scarcity. Optimisation algorithms have been employed to highlight the importance of hyperparameter tuning in improving LSTM convergence and generalisation. For instance, Gong et al. [27] developed an LSTM model optimised by particle swarm optimisation (PSO) using four health indicators (HIs) selected through grey relational analysis. PSO was used to tune hyperparameters, such as neurone numbers, to enhance convergence and prevent overfitting via RMSProp and dropout. The model achieved a 5% accuracy improvement over classical LSTM in experimental datasets. However, this model may not generalise well to batteries with different chemistries or operating conditions. Wang et al. [28] proposed an attention mechanism-enhanced LSTM (AM-LSTM) model. A moving average filter reduced noise in capacity data, and the attention mechanism weighted critical temporal features, improving prediction accuracy. Validated on NASA and University of Maryland datasets, the model demonstrated robustness across diverse battery types and discharge rates. The downside was increased model complexity, which could lead to higher computational costs and longer training times.

Yang and Chen [29] proposed a BiLSTM framework for SOH prediction that integrates time-varying filter empirical mode decomposition (TVF-EMD) and a sliding window to extract nonlinear features and preserve temporal patterns. Hyperparameters were optimised using Bayesian optimisation with hyperband (BOHB), resulting in RMSE < 0.0016 and $R^2 > 0.999$ on NASA datasets (B0005–B0007). The study demonstrated that combining advanced signal processing with bidirectional LSTM significantly improves accuracy compared with LSTM-, SVR-, and CNN-based models. Peng et al. [30] proposed an SOH estimation method that integrates an improved grey wolf optimisation (IGWO) algorithm with an LSTM network to optimise hyperparameters and reduce overfitting. The model used only partial discharging health features (HFs), significantly lowering data requirements and computation time while maintaining accuracy. Experimental results on lithium-ion batteries achieved MAE, RMSE, and MAPE values all within 1%, showing that the IGWO-LSTM framework provided efficient and highly accurate SOH prediction.

Transfer learning further enables application across diverse battery types with limited data. In [31], the author developed a transfer learning-based LSTM approach for SOH and prediction of cycle life across different battery types (NCA and NCM). The model was pre-trained on NCA battery data and adapted to NCM batteries with limited data, reducing the need for extensive retraining. Using NASA and custom datasets, the study achieved high accuracy in capacity fade prediction, with RMSE metrics indicating robust performance. The effectiveness of transfer learning depends on the similarity between source and target battery types. Significant differences in degradation patterns could reduce accuracy. The model also requires pre-training on large datasets, which may not always be available for

new battery chemistries. Yang et al. [32] proposed a GAN-LSTM-TL framework for SOH estimation, where a generative adversarial network (GAN) generated synthetic training data to reduce overfitting and enhance learning. The LSTM network models temporal dependencies, and transfer learning (TL) improves adaptability across different datasets, including NASA and CALCE cells. Experiments showed that GAN-LSTM-TL achieved higher accuracy than standalone LSTM or GAN-LSTM, maintaining prediction errors below 3% even with limited training data.

Hybrid models, such as Hu et al.'s complementary ensemble empirical mode decomposition (CEEMD)–transformer LSTM [33] and Liu et al.'s CNN-BiLSTM [34], improve robustness under diverse operating conditions. Although two datasets were used in [33], both are still within the lab context, field data validation is missing. Also, integrating CEEMD, transformer, and LSTM makes the framework complex and harder to implement or maintain. The use of raw electrochemical impedance spectroscopy (EIS) data in [34] can be resource intensive during the training process because the data are high-dimensional. The model also struggled to predict abrupt capacity drops (e.g., at cycle 190), which may pose safety concerns. Xiang et al. [35] introduced a hybrid model that combines variational mode decomposition (VMD), an extended LSTM (xLSTM), and a frequency-enhanced channel attention mechanism (FECAM) for SOH prediction. The approach used VMD to separate long-term trends from noise, while xLSTM and FECAM jointly captured temporal and frequency-domain features, improving robustness against capacity regeneration and disturbances. Experiments on CALCE and NASA datasets showed the proposed model outperformed LSTM, GRU, BiLSTM, transformer, and CNN-LSTM, achieving MAE as low as 0.0049 and RMSE of 0.0085.

In summary, despite the ability of LSTMs to eliminate the problem of vanishing or exploding gradients, the increased computational complexity requires significant resources, making it less practical for resource-constrained environments. The need for large datasets can be a barrier, and overfitting is a risk without proper regularisation [36]. LSTM also struggles with abrupt changes in battery behaviour, leading to larger errors at high cycle numbers or during rapid degradation. Its black box nature limits interpretability, which can be a major concern in safety-critical battery applications.

2.3. Convolution Neural Network (CNN)

It is a classical feed-forward deep neural network that is used in image recognition, computer vision, and natural language processing, among others. Typically, the network is made up of an input layer, several convolutional layers, subsampling layers, fully connected layers, and an output layer [37]. Figure 3 shows a general hierarchical structure of a CNN.

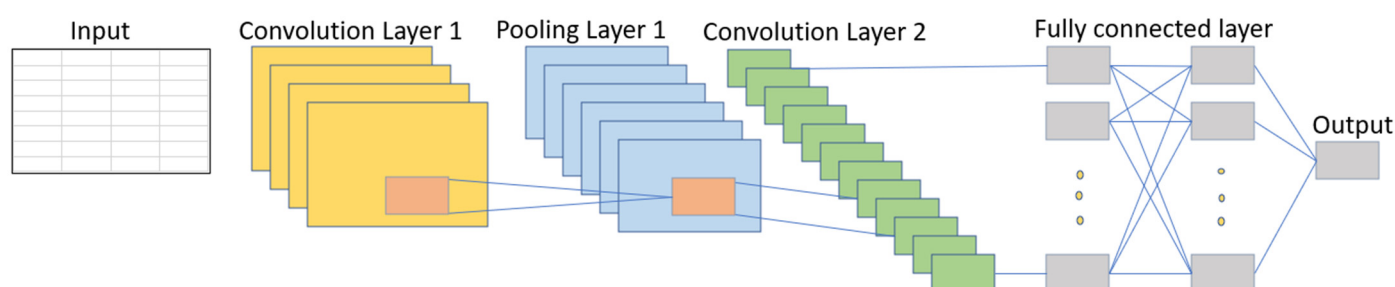


Figure 3. General hierarchy of a convolutional neural network, adapted from ref. [37].

Unlike LSTMs, which excel at sequential modelling, CNNs leverage convolutional layers to extract local patterns, reducing computational complexity and capturing spatial or temporal features, enabling effective feature extraction with lower computational complexity.

The convolutional layers apply filters to the input data to extract features. Each filter slides over the input, computing dot products to produce feature maps. For a 1D input sequence $x \in R^T$, a convolutional layer applies K filters of size F yielding:

$$z_{i,k} = \sum_{j=0}^{F-1} w_{j,k} \cdot x_{i+j} + b_k \quad (11)$$

where w_k is the k -th filter's weights, b_k is the bias, and $z_{i,k}$ is the output at position i for filter k .

ReLU activation introduces nonlinearity given by:

$$a_{i,k} = \max(0, z_{i,k}) \quad (12)$$

The pooling layers reduce spatial dimensions to lower complexity and prevent overfitting. Figure 4 shows a schematic representation of a pooling layer in CNN [38]. Max pooling over a window of size P is given by:

$$p_{i,k} = \max(a_{i,k}, a_{i+1,k} \dots a_{i+P-1,k}) \quad (13)$$

The fully connected layer aggregates features for regression or classification. For regression, the final layer output is given by:

$$\hat{y} = W \cdot h + b \quad (14)$$

where h is the final flattened feature vector, W is the weight matrix, and b is the bias term.

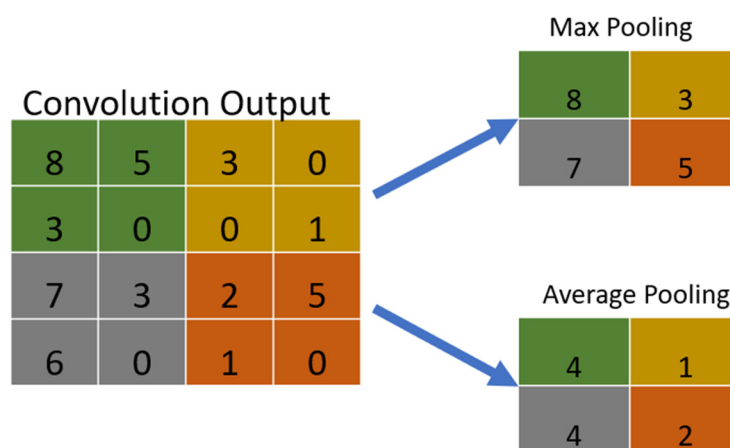


Figure 4. Pooling layer in CNN, adapted from ref. [38].

Recent work highlights a clear progression in CNN-based SOH estimation methods, moving from handcrafted feature design to automated and quantum-enhanced frameworks. Lu et al. [39] demonstrated that extracting and fusing intra-cycle and inter-cycle features from partial voltage curves significantly improves prediction accuracy, with MAE below 0.0028 and MAPE under 0.32%. Bockrath et al. proposed a temporal convolutional network (TCN) for SOH estimation using raw sensor data from partial discharge profiles across different SOC ranges. The TCN processes current and time data directly, avoiding complex preprocessing, and was optimised via Bayesian hyperparameter tuning with stratified cross-validation. Results on NASA randomised battery usage data showed an overall RMSE of 1.0%. Chen et al. [40] simplified feature engineering by applying a CNN directly to partial constant-voltage charging data, showing that only the first 1000 s of CV data was sufficient for highly accurate predictions across different chemistries. Building on these

foundations, Liang et al. [41] proposed a quantum CNN (QCNN) with automated feature fusion using quantum encoding, which achieved $R^2 > 96\%$ across diverse chemistries and operating conditions while reducing parameter requirements. Together, the evolution reflects a shift towards more practical, generalisable, and computationally efficient SOH prediction methods.

CNNs are often combined with other architectures for SOH prediction. Some studies have combined CNN with LSTM, BiLSTM, or attention mechanisms to improve temporal modelling and accuracy. Xing et al. in [42] combined BiLSTM and the attention mechanism with CNN. In [43], the authors used a combination of CNN with LSTM and deep neural networks (DNNs). In the study by Yao et al. [44], it features a hybrid model of CNN, wavelet neural network (WNN), and wavelet LSTM (WLSTM) that inherits both the fast convergence and robust stability of the WNN. In [45], the author combines CNN with the Kolmogorov–Arnold network (KAN). Peng et al. [46] combined CNN-based feature extraction with a probability-sparse self-attention mechanism, reducing computational complexity while capturing both local and long-range degradation features. Tested on cycle life data, including voltage, current, and temperature, the model significantly outperformed traditional models in both accuracy and computational efficiency, showing promise for remote and real-time SOH prediction. These hybrid approaches leverage the strengths of each model, such as robust stability, fast convergence, and improved sequence modelling, to provide better SOH estimation.

Hyperparameter optimisation algorithms have been integrated with CNNs to enhance the performance of SOH prediction. Wu et al. [47] used a multilayer CNN optimised by the Kepler optimisation algorithm (KOA). The model outperformed CNNs without hyperparameter optimisation by up to 58.97% (MAE). It was also noted that increasing CNN depth beyond two layers degraded performance. Despite the high accuracy, KOA adds computational overhead during training, which may not be suitable for systems with limited resources. In [48], the authors propose a hybrid CNN-BiGRU-attention model, optimised using an improved gray wolf optimisation (IGWO) algorithm [49], a tree-structured Parzen estimation (TPE) algorithm is used to optimise the model parameters. The study also used a MC-CNN–TimesNet model where the TimesNet converts 1D time series into a collection of 2D tensors, leveraging multiple cycles to capture intra- and inter-timescale relationships and dependencies and CNN captures deeper spatial. The results indicate that SOH and RUL can be predicted with an average RMSE within 1.5% of features by convolutional operations on the input features. A Bayesian optimisation algorithm was used in [50] to optimise CNN and LSTM and prevent the combined network model from converging to local optima. This model achieved an RMSE of $<1\%$ in the joint validation involving the NASA public dataset and the laboratory self-collected dataset

In summary, CNN is a powerful tool that offers high accuracy and the ability to automatically extract features from complex data. Despite challenges such as data dependency, computational complexity, and limited interpretability, recent advances in hybrid models, multi-modal fusion, and transfer learning enhance CNN's applicability in different applications.

2.4. Random Forest

RF is an ensemble machine learning algorithm that uses multiple decision trees to handle complex battery data, offering robust predictions against noise [51]. RF generates multiple subsets of the dataset through bootstrap sampling (random sampling with replacement). Each subset, typically of the same size as the original dataset, contains a random selection of data points, allowing some samples to be repeated while others are excluded.

This process creates diverse training sets for each decision tree, reducing overfitting and improving robustness.

For each bootstrap sample, a decision tree is constructed. At each node of the tree, a random subset of features (e.g., a subset of voltage, current, or temperature features) is selected to determine the best split, reducing the correlation between trees. The splitting criterion for regression is typically the minimisation of variance, measured by mean squared error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (15)$$

where y_i is the actual SOH and $\hat{y}_i$ is the predicted SOH.

Each decision tree independently predicts the SOH for a given input. For regression, the final SOH prediction is the average of all tree outputs:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T \hat{y}_t \quad (16)$$

where T is the number of trees and $\hat{y}_t$ is the prediction of the t -th tree.

An RF model was built to estimate battery SOH, whose number of regression trees and the number of input variables per node are optimised by the out-of-bag (OOB) estimation [52]. The model used partial data from typical on-board charging conditions but was tested only on two cells from a public dataset. Another study by [53] used RF to predict the state of health of lithium-ion 21,700—5 Ah cells. A grid search was employed to optimise hyperparameters and the model was compared with SVR. The results achieved an R^2 of 0.92 and an RMSE of 0.06. However, the model relies entirely on manually extracted features, which may require extensive domain knowledge. Liang et al. [54] developed an enhanced RF model optimised through PSO to predict the SOH of LiFePO₄ battery modules. The model relies heavily on manual feature extraction from voltage, current, and capacity during charge/discharge cycles, which may limit automation and portability to different datasets. Moreover, even with PSO tuning, RF does not capture temporal dependencies or sequence effects across cycles, thus limiting its ability to track gradual degradation trends. This makes it less suitable for predictive degradation modelling over long-time horizons compared with deep recurrent models.

Lamprecht et al. [55] proposed a novel method that leverages active charge balancing (ACB) behaviour as a degradation indicator and applies RF regression for prediction. Using a modular simulation framework replicating battery aging and balancing processes, their approach achieved high accuracy (1.94% for capacity SOH and 4.28% for resistance SOH), offering one of the few models capable of accurately estimating both capacity fade and resistance growth.

Several recent studies demonstrate the growing effectiveness of hybrid and ensemble learning approaches for SOH estimation. Wang et al. [56] combined RF with gated recurrent u (GRU) to leverage on temporal or spatial features. This led to an improvement in the estimation accuracy and computational efficiency by at least 15.84%. The model, however, depends heavily on the quality and consistency of the input data. The study in [57] used a combined RF–CNN model, which achieved a 34–46% reduction in MAE. The model was validated on specific datasets, so generalisation to different battery chemistries, formats, or use cases (e.g., solid-state, fast-charging) is not guaranteed. Retraining or transfer learning might be needed for new conditions. Lu et al. [58] introduced a transfer learning framework that integrates multi-attention mechanisms, CNN, and RF regression. By using only partial charging segments, freezing CNN feature extraction layers, and replacing dense layers with RF optimised via Bayesian TPE, the method achieved very low RMSE (0.46% for LFP and

1.61% for NCA), reducing estimation errors by up to 80.9%. In [59], RF was used to capture nonlinear relationships and select robust features from voltage, current, temperature, and cycle data; then, the prediction was refined using an artificial neural network (ANN) to extract deeper patterns. The hybrid architecture, however, does not explicitly model time series dependencies or degradation trends over many cycles.

In summary, RF remains a powerful and interpretable that should be paired with robust feature engineering or hybrid architectures for SOH prediction. Its inability to model sequential dependencies and reliance on handcrafted inputs pose challenges for broader deployment in real-time battery health monitoring systems. Future research may focus on combining RF with temporal deep learning models, automated feature extraction, and transfer learning to improve scalability, adaptability, and predictive accuracy across diverse battery types and operating conditions.

3. Discussion

This comparative review highlights the growing importance of ML algorithms in improving the accuracy, adaptability, and robustness of battery SOH prediction. The four models investigated—viz. SVR, LSTM, CNN, and random Fforest—each offer unique strengths and face specific limitations, influencing their suitability in different scenarios. Table 2 shows a summary of the papers used in this literature review.

Table 2. Summary of research showing author, ML algorithm, dataset used and key findings.

1	Zhao et al. (2018) [15]	SVR (RBF)	NASA + CALCE	MAE < 2% SOH; epsilon-insensitive loss helped robustness to outliers/noisy voltage-capacity data.
2	Si et al. (2024) [16]	SVR	Lab datasets	R^2 up to 0.962 on test sets with full discharge; strong performance on partial windows except at high-voltage ranges.
3	Feng et al. (2024) [17]	Hybrid-kernel LSSVR (poly + RBF)	CALCE	Hybrid kernel improved learning/generalisation and helped avoid overfitting vs. single-kernel SVMs.
4	Chen et al. (2023) [18]	PSO-LSSVR (LiFePO ₄ , CC charging)	Partial charge V/I; 2 test cells	Reported MSE < 0.00052, MARE < 0.93%; PSO improved kernel/penalty tuning; robustness to noise/outliers.
5	Liu et al. (2024) [21]	KSVM tuned by nonlinear GWO	Cambridge Cavendish Lab dataset (>20,000 EIS spectra, 12 LR2032 LIBs, 25–45 °C)	GWO-tuned KSVM improved accuracy/stability; longer runtime with larger data.
6	Li et al. (2022) [22]	Improved ant lion optimisation + SVR	NASA	Meta-heuristic tuning enhanced SVR SOH accuracy.
7	Stighezza et al. (2021) [23]	ACO-based SVM (FPGA)	Panasonic 18650PF dataset (NN driving cycle + US06)	Focus is SoC (not SOH); demonstrates hardware feasibility of ACO-SVM.
8	Zhu et al. (2024) [24]	Improved dung beetle optimiser + hybrid-kernel LSSVR (+ VMD)	NASA + CALCE	Hybrid LSSVR + decomposition achieved high SOH accuracy; robust modelling.
9	Gong et al. (2022) [27]	PSO-optimised LSTM (RMSProp + dropout)	Experimental Li-ion; 4 HIs via GRA	~5% accuracy improvement vs. vanilla LSTM; better convergence/overfitting control.
10	Wang, Amogne, Chou, Tseng (2022) [28]	BiLSTM + attention	NASA + Univ. Maryland	Noise-reduced capacity + attention to critical time steps $\Rightarrow$ improved online RUL/SOH robustness across battery types; higher compute cost.

Table 2. Cont.

11	Wang et al. (2023) [31]	Transfer-learning LSTM (NCA→NCM)	NASA + custom (NCA/NCM)	Accurate cross-chemistry SOH/cycle life prediction; depends on source-target similarity and pretraining data size.
12	Hu et al. (2024) [33]	CEEMD–transformer-LSTM	Two lab datasets	Robust accuracy across operating conditions; framework complexity; lacks field validation.
13	Liu et al. (2024) [34]	CNN-BiLSTM (EIS)	Raw EIS	Outperformed GPR, CNN, and LSTM; achieved R^2 up to 0.89 for SOH estimation; enabled early-life RUL prediction from first 50 cycles.
15	Chen et al. (2018) [52]	RF (OOB-tuned)	Sandia National Lab public LFP dataset	RF SOH feasible on partial on-board data; optimisation via OOB; tested on two cells.
16	Amamra (2025) [53]	RF (grid search)	21,700/5 Ah cells	$R^2 = 0.92$, RMSE = 0.06; compared against SVR.
17	Liang et al. (2023) [54]	PSO-optimised RF (LiFePO ₄ modules)	Charge/discharge features	Improved SOH, but heavy manual feature extraction; limited automation/portability.
18	Wang et al. (2024) [56]	RF + GRU (hybrid)	Not specified	Hybrid improved estimation accuracy by $\geq 15.84\%$ vs. standalone RF.
19	Yang et al. (2022) [57]	CNN + RF (hybrid)	Public datasets	34–46% MAE reduction vs. baselines; cautions on generalisation across chemistries/form factors.
20	Bairwa & Roy (2024) [59]	RF + ANN (hybrid)	V/I/T + cycle features	RF for nonlinear features + ANN refinement; does not model long-range sequence dynamics.
22	Xing et al. (2025) [42]	CNN-BiLSTM–attention (EIS)	EIS	Attention + BiLSTM with CNN improves temporal modelling and accuracy under varied conditions.
23	Zraibi et al. (2021) [43]	CNN-LSTM-DNN (hybrid)	NASA + CALCE	Hybrid deep network for RUL/SOH achieved strong performance.
24	Yao et al. (2024) [44]	CNN-WNN-WLSTM (hybrid)	NASA battery datasets (No. 5, 6, 7)	Combines WNN’s fast convergence/stability with WLSTM; robust SOH estimation.
25	Zhang et al. (2024) [45]	CNN-KAN (hybrid)	Lab-generated CC–CV battery cycling data (4 charge rates)	CNN fused with KAN for SOH; improved performance with multi-feature inputs.
26	Wu et al. (2025) [47]	Multilayer CNN + Kepler optimisation (KOA)	Lab datasets	KOA-tuned CNN cut MAE by up to 58.97%; depth > 2 layers degraded accuracy.
27	Liu et al. (2023) [48]	Att-BiGRU (improved GWO)	Real-world EV operational data	Attention-BiGRU with improved GWO delivered comprehensive SOH evaluation/prediction. (GRU noted in CNN section as related.)
28	Li et al. (2025) [49]	MC-CNN-TimesNet + TPE	Multi-cycle time series (2D tensors)	Avg. RMSE within 1.5% by leveraging inter-timescale dependencies.
29	Ding et al. (2025) [50]	Bayesian-optimised hybrid NN (CNN + LSTM)	NASA + lab	BO prevented local minima; RMSE < 1% in joint validation.
30	Chen, Kollmeyer, Ahmed, Emadi (2025) [60]	CNN with TL + multi-modal fusion	Partial voltage profiles + histograms	Transfer learning + multi-modal fusion improved SOH; supports re-use across datasets.

Table 2. Cont.

31	Vedhanayaki & Indragandhi (2025) [19]	Bayesian optimised SVR (BO-SVR) with Gaussian kernel	NASA B0005	Achieved RMSE = 0.0082, outperforming standard SVR and GPR; Bayesian optimisation improved efficiency.
32	Peng et al. (2025) [46]	Convolutional-ProbSparse-transformer (CPT)	NCM (BN-74, BN-100) + public datasets	$3.2\times$ faster training vs. transformer; accuracy $\uparrow$ 112%; robust for long-term prediction
33	Chen et al. (2023) [40]	CNN with partial CV charging + TL	Multi-chemistry dataset	Only first 1000 s of CV data needed; accurate SOH prediction; transfer learning improved generalisation
34	Lu et al. (2024) [39]	Feature fusion CNN (capacity-voltage + derivatives)	18 batteries, 3 datasets	$MAE \leq 0.0028$, $MAPE \leq 0.32\%$; intra-cycle + inter-cycle features improved accuracy.
35	Yang et al. (2022) [32]	GAN-LSTM-transfer learning	NASA+ CALCE	Errors < 3%; GAN mitigated data scarcity, TL improved cross-dataset adaptation
36	Xiang et al.(2025) [35]	VMD + xLSTM + FECAM hybrid	CALCE+ NASA	$MAE = 0.0049$, $RMSE = 0.0085$, outperformed LSTM, GRU, transformer.
37	Yang and Cheng (2025) [29]	TVF-EMD + BiLSTM with BOHB tuning	NASA B0005-B0007	$RMSE < 0.0016$, $R^2 > 0.999$, better than CNN-LSTM, SVR; robust across datasets.
38	Xia et al. (2025) [20]	Sine-SSA optimised SVR with EIS-based feature selection	Commercial EIS dataset (>20 k samples, 25–45 °C)	Max error = 2.58%, outperforming LSTM, GPR; robust under varying temperatures.
39	Lamprecht et al. (2020) [55]	RF regression	Simulated Tesla Model S battery pack (96S74P, 85 kWh) with aging + charge balancing framework	Achieved 1.94% error for capacity SOH and 4.28% for resistance SOH, outperforming other ML methods.
40	Lu et al. (2024) [58]	CNN + attention + random forest with transfer learning	Oxford dataset (LCO pouch cells), Sandia dataset (LFP, NCA 18,650 cells)	Reduced estimation errors by 80.9% (LCO), 41.3% (LFP), and 25.6% (NCA). Achieved very low RMSE (0.46% for LFP).

SVR stands out for its strong performance on smaller datasets and its robustness to outliers, making it suitable for early-stage SOH estimation and low-resource environments [25]. However, its inability to capture temporal dependencies and its sensitivity to kernel parameter tuning limit its application in long-term or dynamic battery use cases. Advances in hybrid kernel functions and optimisation algorithms (e.g., PSO, GWO) have improved its performance, yet scalability remains a concern.

LSTM networks are well-suited for sequential modelling, particularly in capturing long-term dependencies in degradation trends. However, they are computationally intensive, require large volumes of labelled data, and suffer from interpretability issues [26]. Hybrid models that combine LSTM with attention mechanisms or signal decomposition techniques (e.g., CEEMD) have demonstrated superior accuracy, though at the cost of increased model complexity.

CNNs offer an effective framework for extracting spatial features and handling complex high-dimensional input data. When applied to voltage, current, or EIS signals, CNNs can automatically derive salient features that contribute to accurate SOH prediction. However, they struggle with temporal dependencies when used in isolation. Consequently, CNNs are most effective when integrated with temporal models such as LSTM or BiLSTM, enabling robust spatiotemporal learning [60].

Random forest remains a reliable and interpretable model, particularly useful in scenarios where data are limited or noisy. It is computationally efficient and easy to

implement but lacks the ability to model degradation trends over time [61]. To overcome this, RF is often combined with recurrent models (e.g., GRU) or deep networks (e.g., CNN or ANN) to improve its temporal modelling capability and generalisability across battery chemistries and usage patterns.

In general, hybrid models, such as CNN-LSTM, RF-GRU, and CNN-KAN, have shown promise by combining the strengths of individual algorithms. These architectures have achieved better generalisation, robustness, and accuracy in SOH estimation. However, they introduce trade-offs in terms of complexity, computational cost, and training time. Therefore, the choice of model should be guided by specific application requirements, including the data availability, the target hardware constraints, and the desired prediction horizon. Newer studies have focused on newer hybrid frameworks and optimised-assisted models.

While this study only compared SVR, RF, CNN, and LSTM, some of the recent literature has demonstrated the potential of transformer-based architectures and extreme learning machine algorithms for SOH estimation. For instance, Duan et al. [62] developed a variable forgetting factor online sequential extreme learning machine (VFOS-ELM), optimised using an improved whale optimisation algorithm (IWOA) for SOH estimation and remaining useful life prediction. The hybrid framework achieved RMSE below 0.15% and exhibited strong adaptability across NASA, Oxford, and MIT datasets. Shu et al. [63] introduced a voltage-segment transformer framework, achieving sub-2% errors using only partial charging data, thus making the approach practical for EV scenarios. Chen et al. [64] further demonstrated the adaptability of transformers in an edge–cloud collaborative SOH framework. By coupling a variational mode decomposition (VMD) step with MEWOA optimisation and a pre-LN transformer, they achieved MAE < 0.6% and MSE < 0.008% across NASA, CALCE, MIT, and EV field data. Their ability to model both short-term fluctuations and long-term degradation trends suggests that future BMS implementations may increasingly adopt transformer variants, particularly in edge–cloud collaborative frameworks.

Interpretability, data scarcity, and transferability remain critical challenges. Many high-performing models such as CNNs and LSTMs function as black boxes, limiting their adoption in safety-critical applications such as electric vehicles. Additionally, most studies rely on public laboratory datasets, which may not reflect real-world operating conditions. Efforts to integrate physics-informed features, enable online learning, and apply transfer learning are key to improving model robustness and deployment across diverse battery chemistries, formats, and environmental conditions. Some of those efforts can be seen in studies such as [65], which proposed an enhanced 1D-CNN framework that uses variable-length charging segments to mimic user random charging behaviour and integrates transfer learning for adaptability across different chemistries.

To address the challenge of explainability, SHAP (SHapley Additive exPlanations) and LIME (local interpretable model-agnostic explanations) [66] that are both popular explainable AI (XAI) have been explored. Jafari and Byun [67] applied SHAP to a CNN-LSTM-ConvLSTM fusion model, showing that SOH predictions can be decomposed into physically meaningful contributions from capacity, voltage, current, and temperature. Similarly, M.K. B et al. [68] introduced the CART-GX hybrid model, where SHAP gradient explainer revealed consistent feature importance across NASA and CALCE datasets. Notably, they argued that SHAP is more robust than LIME, whose explanations may vary with small perturbations. Together, these studies show that SHAP offers both interpretability and stability, bridging the gap between high-performing deep models and practical BMS requirements.

4. MATLAB Simulations

4.1. Introduction to the Datasets

This article uses the NASA battery dataset for the simulations [69]. It consists of four lithium-ion battery datasets labelled as B0005, B0006, B0007, and B0018 with a rated capacity of 2 Ah and a rated voltage of 3.7 V. These four batteries were subjected to charge/discharge experiments at 24 °C using a constant current–constant voltage charging protocol at 1.5 A until 4.2 V, followed by a constant voltage phase until the current dropped below 20 mA. Discharge was performed under a constant current of 2.0 A down to 2.7 V (B0005), 2.5 V (B0006), 2.2 V (B0007), and 2.5 V (B0018). The time series cycle measurements of voltage (V), current (I), temperature (T), and capacity (Ah) were recorded until end-of-life, which is defined as the point when the measured capacity drops below 70% of nominal capacity.

Figure 5 illustrates the capacity degradation curves of the four batteries. For each battery, the discharge capacity decreases progressively with cycling. This degradation is used to construct the SOH labels. Specifically, SOH is calculated as

$$\text{SOH} = \frac{C_i}{C_0} \times 100\% , \quad (17)$$

where C_i is the discharge capacity at the current cycle and C_0 is the initial nominal capacity. Figure 6 shows the raw SOH degradation curves. The degradation curves highlight several important aspects of lithium-ion battery ageing. First, the degradation is nonlinear, with an initial period of gradual decline followed by accelerated capacity loss near end of life. This behaviour reflects the combined effects of electrode degradation, electrolyte decomposition, and loss of active material. Second, variation across the cells can be observed, even under identical cycling conditions, underscoring the influence of inherent manufacturing differences and stochastic degradation mechanisms.

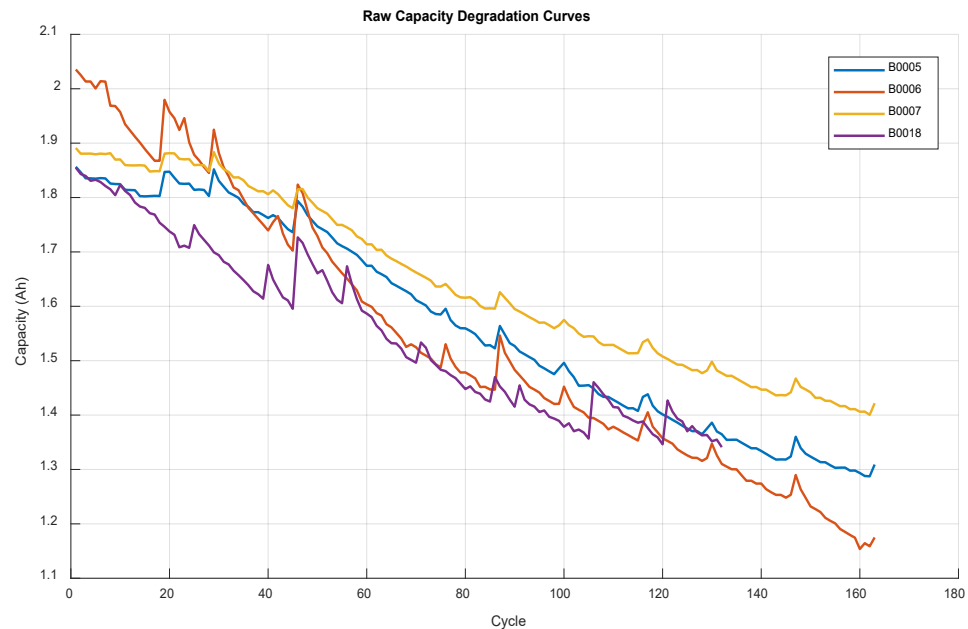


Figure 5. Raw capacity degradation curves.

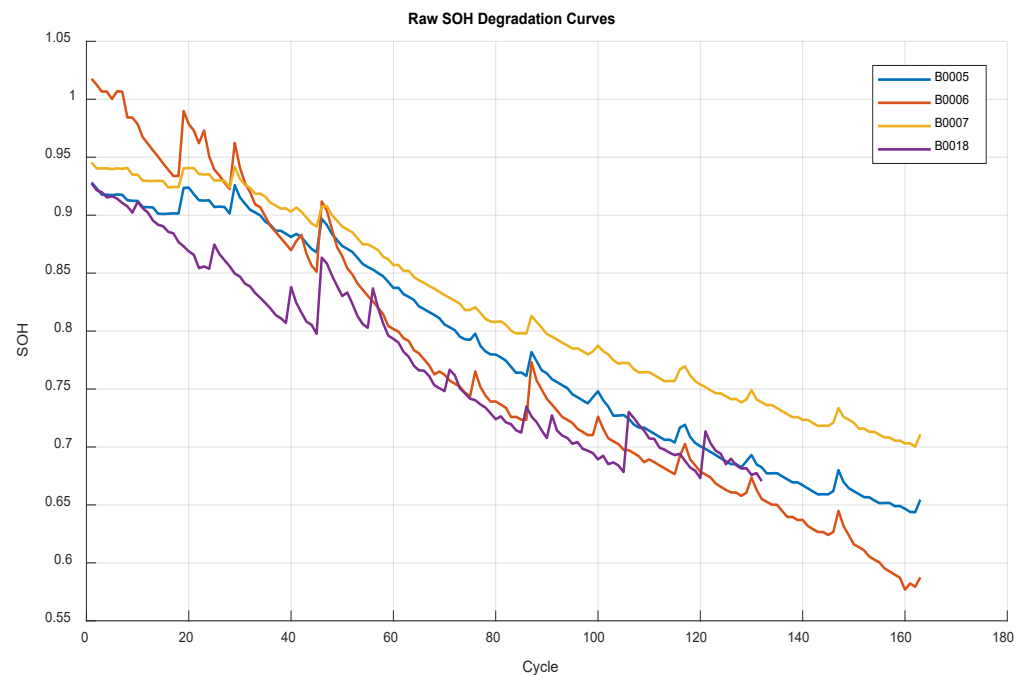


Figure 6. Raw SOH degradation curves.

These trends justify the use of machine learning approaches, as traditional models often struggle to capture such nonlinear and cell-specific ageing patterns. The inclusion of B0005 as the independent test set further emphasises the need for generalisable models, to ensure fair comparison, since predictive accuracy must extend across batteries with similar but not identical degradation trends. For this paper, B0006, B0007, and B0018 were used as the training data and B0005 was used as the testing data.

4.2. Health Features Extraction

The extraction of health features from discharge cycles followed a standardised process to achieve model comparison fairness.

i. Resampling to a fixed length

The raw dataset contains discharge cycles that have varying time steps because of different sampling rates and cycle lengths. To make the cycles comparable, all signals were resampled to 120 uniformly spaced points along a normalised time axis (0 to 1). The normalisation process maintains the original degradation patterns while removing the effects of varying cycle lengths.

ii. Measurement signals

From the resampled signals, six synchronised sequences were constructed: the raw measurements of voltage (V), current (I), and temperature (T), together with their first-order derivatives with respect to time (dV/dt , dI/dt , dT/dt). This produced a 6×120 representation per cycle, capturing both the original signal values and their time-dependent variations.

iii. Use across models

- **CNN and LSTM:** The full 6×120 sequences were provided directly as inputs, enabling the networks to learn both local patterns (via convolution) and temporal dependencies (via recurrent layers).
- **SVR and RF:** Since these models require vectorised features rather than full sequences, summary statistics were computed from the same 6×120 representation. These features are shown in Table 3, which gives a summary of the health features that were used in the SVR and RF models.

Table 3. Summary of the extracted health features and their definitions.

Feature Name	Mathematical Expression	Definition of Symbols
Mean	$\bar{x} = \frac{1}{T} \sum x_t$	x_t : signal at time t : for each signal $x \in \{V, I, T, dV, dI, dT\}$; T : number of samples
Standard deviation	$\sigma_x = \sqrt{\frac{1}{T-1} \sum (x_t - \bar{x})^2}$	$\bar{x}$: mean of signal
10th percentile	$x_{10} = \text{percentile}(x, 10)$	10% quantile of all x_t values
90th percentile	$x_{90} = \text{percentile}(x, 90)$	90% quantile of all x_t values
Quartile slopes	$\frac{V_{50}-V_{25}}{0.25}, \frac{V_{75}-V_{50}}{0.25}$	V_{25}, V_{50}, V_{75} : voltages at 25%, 50%, and 75% of discharge
Overall voltage slope	$\frac{V_{90}-V_{10}}{0.8}$	V_{10}, V_{90} : voltages at 10% and 90% of discharge
Maximum rate of change	$ dV _{\max} = \max dV_t $	$dV_t = V_t - V_{t-1}$: voltage derivative
Peak-to-peak derivative amplitude	$dV_{ptp} = \max(dV_t) - \min(dV_t)$	dV_{ptp} : peak-to-peak derivative voltage
Correlation (V, I, T)	$\frac{\text{cov}(V,I)}{\sigma_V \sigma_I}, \frac{\text{cov}(V,T)}{\sigma_V \sigma_T}, \frac{\text{cov}(I,T)}{\sigma_I \sigma_T}$	$\text{cov}(\cdot, \cdot)$: covariance between signals

All the extracted features were retained to preserve physical interpretability and ensure a fair and consistent basis for model comparison. No feature selection was carried out. This design ensured that all models learned from the same physical information, with differences arising only from the modelling approach rather than from variations in input features. The objective was to capture both the absolute values of key electrochemical signals and their dynamic behaviour, while ensuring consistency across cycles of different lengths.

4.3. Model Training

- CNN: A 1D convolutional neural network with three convolutional layers, batch normalisation, global average pooling, and fully connected layers, trained for 100 epochs with early stopping on validation loss
- LSTM: A stacked bi-directional LSTM network, followed by fully connected and dropout layers, trained for 60 epochs with similar validation protocol.
- SVR: The RBF kernel was used with grid search performed over the hyperparameters (C, ϵ , kernel scale) tuned via 5-fold cross validation, and the best model refit on full training data.
- RF-TreeBagger regression with hyperparameters (number of trees, minimum leaf size) chosen via grid search and out-of-bag RMSE minimisation.

Both CNN and LSTM models were optimised using the Adam optimiser with an initial learning rate of 5×10^{-4} and a regularisation coefficient of 10^{-4} . B0005 was held out entirely for testing, ensuring cross-battery generalisation.

Validation is performed using a subset of the training data, with early stopping for deep models to avoid overfitting. Classical models are trained on the complete training set. A summary of the search space used and the final values of the hyperparameters is given in Table 4

Table 4. Summary of the hyperparameters used for each ML model.

ML Model	Hyperparameters	Hyperparameters Search Space	Final Value Used
Random Forest (RF)	Number of trees	{300, 600, 800}	600
	Minimum leaf size	{1, 2, 4}	2
Support Vector Regression (SVR)	C	{1, 10, 100}	10
	ϵ	{0.01, 0.03, 0.1}	0.03
	Kernel	{0.3, 1, 3}	1
CNN	Convolution filters	Conv filters: [64 (k = 7), 128 (k = 5), 128 (k = 3)];	Conv1D(64,7)
			Conv1D(128,5)
			Conv1D(128,3)
	FC layer size	{128, 256}	256
	Dropout	{0.2, 0.3}	0.3
	Epochs	{80, 100, 120}	100
	Batch size	{16, 32}	32
BiLSTM	Hidden units	{64, 128}	biLSTM(128, sequence)
			biLSTM(64, last)
	Layers	{1, 2}	2
	Dropout	{0.25, 0.3}	0.25/0.3
	FC layer size	{64, 128}	128
	Epochs	{50, 60, 80}	60
	Batch size	{8, 16}	16

4.4. Evaluation

All models were tested on the independent test battery (B0005). Performance was assessed using metrics such as R-squared (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). These metrics provide separate statistical measures to evaluate model accuracy and the strength of the relationships between predictor variables and target outcomes.

(a) Mean Absolute Error (MAE)

The mean absolute error (MAE) measures the average discrepancy between forecasted and actual values to show how much predictions differ from real outcomes.

The MAE can be formulated as follows:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \quad (18)$$

where y_i and $\hat{y}_i$ are the actual and predicted values, respectively. A lower MAE score signifies improved model performance. Mean absolute percentage error (MAPE) expresses the average magnitude of error as a percentage of the actual values.

(b) R-squared (R^2)

The R-squared value, also known as the coefficient of determination, represents the proportion of variance in the dependent variable that is predictable from the independent variables. It is given by,

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (19)$$

(c) Root Mean Squared Error (RMSE)

The root mean squared error (RMSE) measures the square root of the average of squared differences between predicted and actual values. It is widely a key metric for assessing regression-based ML models. Generally, RMSE and MAE metrics indicate the variability of residuals, while R^2 values represent how well the model fits the data:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (20)$$

4.5. SOH Estimation Results and Discussion

4.5.1. Performance Metrics

Table 5 summarises the predictive accuracy of the four models on the independent test battery (B0005). The LSTM model achieved the best overall performance, with the lowest RMSE, MAE, and MAPE, and the highest R^2 , indicating superior accuracy in SOH estimation. The CNN model also performed very well, slightly below LSTM but outperforming the RF and SVR models. Random forest (RF) performed comparably to CNN, demonstrating the effectiveness of tree-based ensembles with engineered features. Support vector regression (SVR) showed significantly higher error rates and lower R^2 , suggesting a weaker capacity for capturing nonlinearities and sequence-dependent patterns in the data.

Table 5. Performance metrics across the ML models.

Model	RMSE	MAE	R^2	MAPE (%)
CNN	0.0194	0.0160	0.964	1.84
LSTM	0.0146	0.0118	0.980	1.39
SVR	0.0457	0.0392	0.800	4.80
RF	0.0207	0.0172	0.959	2.15

4.5.2. Predicted vs. Actual SOH Across the Different ML Models

Figure 7 illustrates the predicted versus actual SOH trajectories for each model on the independent test battery (B0005). Across all models, the overall degradation trend was captured with varying levels of accuracy. The random forest (RF) model aligned well with the actual SOH during mid-life cycles but diverged in later stages, consistently underestimating the SOH. This behaviour reflects RF's strength in modelling global nonlinear relationships, but also its limitation in representing sequential dependencies inherent in degradation processes.

The support vector regression (SVR) model failed to capture sharper declines in SOH during late-life cycles, leading to systematic overestimation near end of life. While SVR remains effective for regression tasks, its static formulation makes it less suitable for long-term time-dependent battery dynamics.

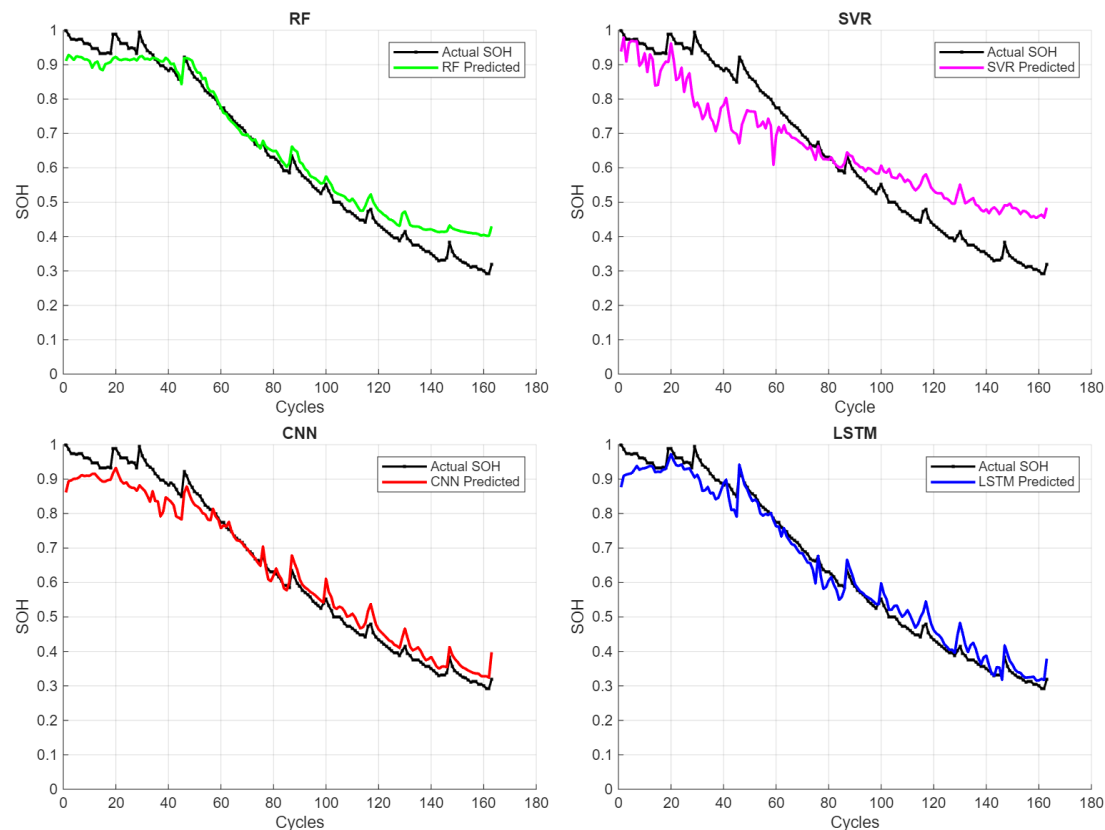


Figure 7. Predicted vs. actual SOH across the different ML models.

In contrast, the deep learning models achieved stronger performance. The convolutional neural network (CNN) showed close agreement with the actual SOH, particularly during mid-life cycles, and effectively extracted local degradation features. However, its reliance on convolutional filters constrained its ability to capture long-range temporal dependencies, resulting in deviations in later cycles. The long short-term memory (LSTM) network provided the closest alignment with the true SOH across the entire cycle range. The success of LSTM is not only because of its sequence modelling capabilities but also because it captures the inherent time-related physical–chemical processes during battery aging (such as SEI film growth and lithium deposition), which have strong memory effects and timing dependence.

By exploiting its memory mechanism and its ability to model sequential dependencies, LSTM produced smooth and accurate predictions, even during sharp capacity declines. This indicates strong robustness in both short- and long-term SOH tracking. In comparison, RF demonstrated the utility of ensemble methods when combined with engineered statistical features, though it lagged behind CNN and LSTM. SVR struggled to generalise across different batteries, reflecting its sensitivity to kernel selection and its limited flexibility in modelling degradation trajectories.

Quantitatively, LSTM achieved the lowest error values (RMSE and MAE, see Figure 8), followed by CNN, RF, and SVR. These findings reinforce that models explicitly designed for sequential data offer superior performance compared with classical machine learning techniques in battery prognostics.

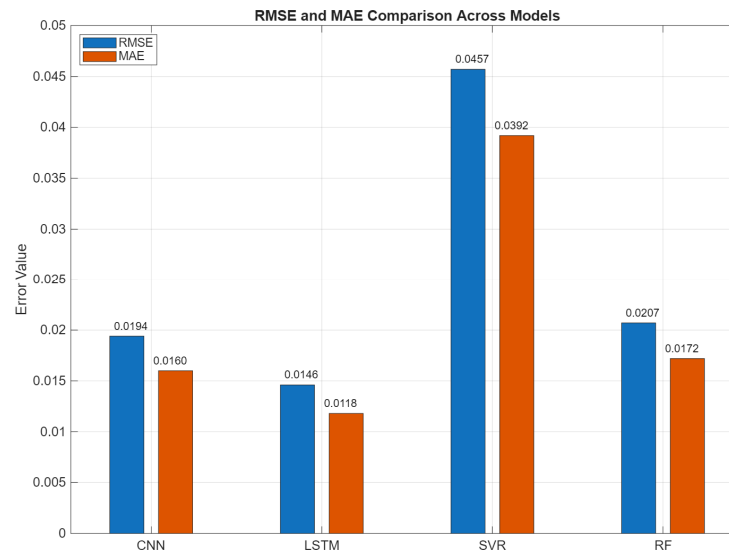


Figure 8. Bar graph showing RMSE and MAE across all the models.

From a practical perspective, accurate SOH prediction is essential for the safe and efficient use of lithium-ion batteries in electric vehicles and stationary energy storage. LSTM's superior accuracy suggests strong potential for integration into battery management systems (BMSs), where reliable long-term forecasting is critical for maintenance planning, failure prevention, and extended service life. However, their high computational and memory demands make direct deployment on embedded BMS hardware challenging. Efficiency can be improved through lightweight strategies such as pruning, quantisation, knowledge distillation, or hybrid offline–online frameworks. Nonetheless, models such as RF and SVR remain relevant in resource-constrained applications due to their lower computational requirements.

4.5.3. Training Time

The evaluation process also included an assessment of computational efficiency. As expected, the training times for SVR and RF were significantly shorter than for deep learning models, as shown in Table 6. The SVR and RF models trained very quickly, typically within seconds to a minute, on a typical workstation equipment. The training duration for CNN and BiLSTM models took longer than the other models due to their larger parameter space and iterative optimisation, though this additional cost was compensated by higher predictive accuracy. Despite these differences in training, all models in this evaluation demonstrate sufficient real-time SOH estimation capabilities.

Table 6. The training time of the four machine learning models.

ML Model	Training Time (s)
CNN	57.95
SVR	5.29
RF	26.11
LSTM	201.59

5. Conclusions

This review compared machine learning methods for lithium-ion battery SOH estimation, supported by MATLAB simulations on the NASA B0005, B0006, B0007, and B0018 dataset. The results showed that LSTM achieved the highest accuracy (RMSE = 0.0145,

MAE = 0.0118, $R^2 = 0.980$, MAPE = 1.39%), followed by and CNN and RF, while SVR lagged behind (RMSE = 0.0457, MAE = 0.0392, $R^2 = 0.800$, MAPE = 4.80%). These findings are consistent with the literature, where sequence-based models such as LSTM and BiLSTM demonstrate superior ability to capture temporal degradation, while RF and CNN remain competitive. Support vector regression (SVR) showed weaker generalisation and struggled with sequence-dependent degradation patterns

Across published studies, optimisation algorithms (PSO, SSA, Bayesian methods) and hybrid models (CNN-LSTM, CNN-WNN-WLSTM, IGWO-LSTM) further improve accuracy, often reducing prediction errors below 1%. Emerging methods such as transformers, transfer learning, TCNs, and QCNns indicate a shift toward models that combine local feature extraction, long-range dependency modelling, and computational efficiency.

The findings confirm that deep learning approaches, particularly those designed for sequential data, outperform classical machine learning methods in SOH estimation. Nevertheless, classical algorithms such as RF and SVR remain useful in contexts where computational efficiency and simplicity are prioritised. The results of both the literature review and simulation highlight the potential of hybrid models, which integrate complementary strengths of individual models to improve accuracy, robustness, and efficiency.

Future research should address several open challenges in the application of ML for battery SOH estimation:

- **Interpretability and Trust:** Deep models such as LSTM and CNN remain black box in nature. Incorporating explainable AI techniques (e.g., SHAP, LIME) [70] can enhance transparency and facilitate adoption in safety-critical applications.
- **Model Robustness and Real-World Applicability:** The simulations in this study used only the controlled NASA PCoE dataset (25 °C, fixed charge/discharge protocols), which does not fully represent real-world EV conditions such as fluctuating temperatures, dynamic load profiles, and irregular charging. Future work should validate these models on field datasets to assess robustness. Transfer learning and domain adaptation should be further explored to improve generalisation across chemistries and usage conditions [71].
- **Hybrid and Physics-Informed Models:** Combining machine learning with physics-informed features [72] or models can improve accuracy while reducing data requirements, creating more generalisable frameworks.
- **Resource-Constrained Deployment:** Simplified models (e.g., RF or lightweight neural networks) should be optimised for embedded deployment in battery management systems (BMSs), especially in low-cost EVs and grid storage applications.
- **Long-Term Prognostics:** Future work should extend beyond short-term SOH estimation to include reliable prediction of remaining useful life (RUL) [62], which is critical for lifecycle optimisation and predictive maintenance.

Author Contributions: Conceptualisation, L.M. and K.R.; methodology, L.M. and K.R.; software, L.M.; validation, L.M., K.R. and A.B.; formal analysis, L.M.; investigation, L.M.; resources, K.R. and A.B.; writing—original draft preparation, L.M.; writing—review and editing, K.R. and A.B.; visualisation, L.M.; supervision K.R. and A.B.; project administration, K.R. and A.B.; funding acquisition, K.R. and A.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the European Union's Intra-Africa Academic Mobility Scheme under the grant agreement No. 101144276—NeDMEV. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Education and Culture Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

Data Availability Statement: The data supporting the results of this study were obtained from the NASA Prognostics Center of Excellence (PCoE). Available online: <https://www.nasa.gov/intelligent-systems-division/discovery-and-systems-health/pcoe/pcoe-data-set-repository/> (accessed on 1 August 2025).

Acknowledgments: During the preparation of this manuscript, the authors used Chatgpt-4.5 for the purposes of refining the manuscript's language, improving clarity, and enhancing overall readability. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

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