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Physics-Informed and Brain-Inspired Set-Routed Neural Networks for Lithium-Ion Battery Life-Cycle Assessment in Medical Devices

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Abstract: This work presents a dual-purpose study. The first objective is to generate a realistic synthetic dataset for battery health monitoring. The second objective is to validate both the realism of the dataset and the performance of a novel neural architecture, termed the Set-Routed Neural Network (SetNet), for regression-based estimation of State of Health (SOH) in medical-grade energy storage devices. The dataset comprises 20 complete life cycles, each containing approximately 50,000-time steps with recorded electrical, thermal, and state parameters including Current (A), Voltage (V), Temperature (°C), State of Charge (SOC), and SOH. To ensure realism, statistical validation and frequency-domain analyses confirmed physically plausible behavior, with a mean voltage of $3.89 \text{ V} \pm 0.08$, mean temperature of $25.08 \text{ °C} \pm 0.20$, and SOC distributions consistent with operational ranges. In the learning phase, SetNet was benchmarked against a standard Multilayer Perceptron (MLP) using an 80/20 train-test split over all life cycles. Results show that SetNet achieved an RMSE of 0.0496, MAE of 0.0412, and an R^2 score of 0.2639, outperforming the MLP baseline (RMSE 0.0872, MAE 0.0679, R^2 0.275). The smooth convergence curves and stable mini-batch loss observed in SetNet indicate superior generalization and robustness. These findings highlight SetNet's ability to route features selectively across modular subnetworks, enabling efficient modeling of multi-domain interactions (electrical–thermal–chemical) inherent in medical battery systems. Overall, the proposed architecture establishes a biologically inspired, interpretable foundation for predictive maintenance and reliability assessment in future medical energy systems.

Keywords: battery health monitoring; bio-inspired computing; lithium-ion; medical devices; set-routed neural networks; state of health

1. Introduction

In the last decade, the advancement of energy storage systems has not only transformed transportation and renewable energy but has also become pivotal in the medical technology sector. Modern medical devices such as implantable cardiac defibrillators, pacemakers, insulin pumps, portable ventilators, and diagnostic imaging equipment increasingly rely on high-performance lithium-ion batteries to ensure reliability, precision, and patient



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safety. These systems demand uninterrupted operation, compact size, lightweight construction, and exceptional long-term stability, characteristics that have positioned lithium-ion chemistry as the preferred choice. As illustrated in Figure 1, lithium-ion batteries' high energy density, stable voltage characteristics, and scalability make them indispensable for powering a wide range of medical technologies, from portable diagnostic tools to critical life-supporting implantable devices [1–4].

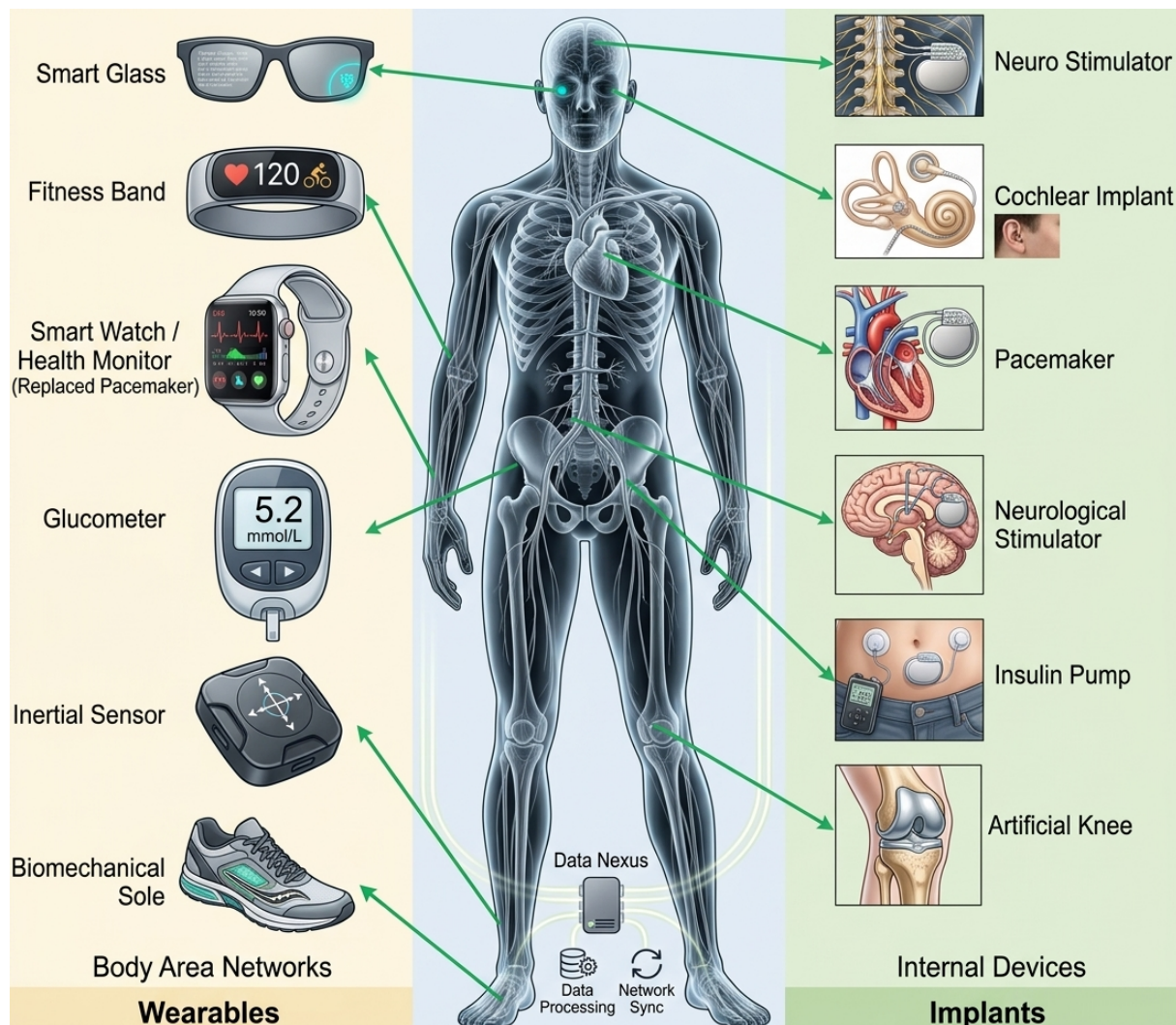


Figure 1. Various wearable and implantable medical devices commonly employed in precision healthcare applications (Inspired from [5]).

However, unlike consumer electronics or electric vehicles, the failure of a medical battery carries direct consequences for patient health and safety, underscoring the critical importance of continuous monitoring and SOH estimation. Accurate prognostics allow for early fault detection, predictive maintenance, and compliance with stringent healthcare safety standards. Consequently, the development of robust, intelligent battery health management systems capable of operating reliably in constrained embedded environments has become an essential research frontier in medical device engineering [6–9]. A crucial metric in this regard is SOH, typically defined as the measure of battery aging (often capacity loss or internal resistance increase) relative to its initial or rated condition [10]. It is a quantification of the battery's degradation relative to its original capacity (known as healthy capacity) and internal condition. Truthful SOH prediction enables better battery management, preventive maintenance, optimization of usage strategies, extension of lifetime, and avoiding catastrophic failures. However, despite decades of effort, accurate SOH prediction remains a significant challenge. Based on a broad review of the literature on SOH prediction (also known as SOH estimation), existing methods can be classified into three major methodological categories: (i) model-based (physics or equivalent circuit), (ii) data-driven, and (iii) hybrid/fusion approaches combining aspects of both. Several recent review papers have classified accordingly [11–13]. Below we summarize each category and highlight their respective strengths and limitations.

Model-based approaches are generally derived from physical/chemical modelling or equivalent circuit representations of the battery. These typically attempt to capture degradation via internal parameter evolution (e.g., changes in resistance, capacitance, diffusion parameters, etc.). The advantage of model-based methods is that they offer interpretability and connection to the underlying physics or mechanisms of ageing; they often require fewer data for calibration under known conditions. But the disadvantages include: high modelling complexity; difficulty in capturing real-world usage variation and latent/unmodelled phenomena; parameterization drift under varying conditions; and typically limited generalizability to unseen chemistries or operating regimes [13]. In contrast, data-driven methods focus on mining measurements (voltage, current, temperature, impedance, capacity fade curves etc.) to directly estimate and predict SOH without explicitly modelling all underlying physics. These cover conventional machine learning and deep learning algorithms [14]. Data-driven methods generally offer high predictive accuracy when sufficient quality data are available, and are relatively straightforward to deploy once the model is built [15]. However, they suffer from the need for large amounts of labelled data. In fact, full cycles and degraded states are often required. In addition, the extracted features may lack physical interpretability; generalization to unseen operating regimes or chemistries is challenging. Besides, data noise or measurement errors can degrade performance [13–16]. Moreover, purely data-driven models may lack mechanistic insight, making them less robust under shifting conditions [17]. Hybrid (or fusion) methods attempt to combine the best of both worlds: the interpretability and mechanism insight of model-based methods, plus the flexibility and accuracy of data-driven methods. Such approaches might embed a physical model with parameters that are then tuned via machine learning, or use a model to generate features which are then fed into a machine-learning predictor, or combine ensemble methods across both categories [18]. Hence, in a recent review, authors emphasize the trend of integrating empirical measurement, model-based estimation, and artificial intelligence fusion techniques [19]. The hybrid approach is widely viewed as the next frontier given the increasing complexity of real-world applications considering variable industrial conditions of temperature, ageing regime, partial cycles and domain shifts. However, this approach presents some drawbacks such as the high computational cost, the computation complexity, the harmony between models and Artificial Intelligence (AI) generation, etc. [20,21].

The prediction of lithium-ion battery SOH is critical due to the widespread use of batteries and the need for safe, reliable, and cost-effective operation. While model-based methods offer interpretability and data-driven methods provide high accuracy, the complexity of real-life battery aging and variable usage conditions favors hybrid, mechanism-informed approaches [22]. Lithium-ion batteries are increasingly deployed in biomedical devices such as pacemakers, neurostimulators, drug delivery systems, and wearable biosensors, where compact, long-lasting, and safe energy storage is essential [23–26]. Their high energy density, stable voltage output, long cycle life, low self-discharge, and rapid charging enable fully implantable closed-loop systems and seamless wearable sensing, overcoming traditional battery limitations. Because these batteries can be life-sustaining, failures have far more serious consequences than in consumer electronics, making accurate SOH estimation a clinical imperative. Recent advances in machine learning offer promising pathways for Prognostics and Health Management (PHM), allowing early detection of degradation, reducing surgical interventions, and ensuring device reliability [27–29]. However, many current models lack biological plausibility, interpretability, or generalizability, highlighting the need for hybrid approaches that integrate neural architectures with the robustness and efficiency required for medical-grade applications.

In this study, we aim to address two critical challenges in the field of lithium-ion batteries for medical devices. First, there is a notable scarcity of high-quality datasets specifically designed for implantable and portable biomedical applications, despite their importance for patient safety and device reliability. Second, traditional neural network architectures often struggle with efficiency, interpretability, and robustness when applied to battery SOH prediction in real-world, multi-domain conditions. Our work targets both of these gaps by combining rigorous dataset generation with innovative, biologically inspired machine learning models.

In this context, the main contributions of this study can be outlined as follows:

(1) Development of a Medical Battery Dataset:

- Generated physics-informed data capturing voltage, current, temperature, and SOC dynamics.
- Incorporated realistic noise and variability to reflect operational conditions of implantable devices.
- Validated dataset through time-domain, frequency-domain, and statistical analyses to ensure reliability and usability for algorithm benchmarking.

(2) Brain-Inspired Neural Network Architecture (SetNet):

- Designed SetNet to mimic modular and sparse connectivity of biological neurons.
- Processed subsets of battery features (electrical, thermal, and state variables) independently before merging, improving learning efficiency and robustness.

- Enabled real-time, non-invasive SOH estimation without frequent recalibration, suitable for smart implantable biomedical devices.
- Closing Paragraph

Collectively, these contributions provide a foundation for next-generation medical devices capable of autonomous monitoring and predictive maintenance. By integrating a realistic, multi-domain dataset with the SetNet architecture, we enhance both the fidelity of SOH predictions and the reliability of the underlying models. While our focus is on medical applications, the approach is broadly applicable to other high-reliability systems, including aerospace, autonomous robotics, and other safety-critical domains where efficiency, interpretability, and robustness are paramount.

A range of practical data-driven approaches have been proposed for battery state-of-health (SOH) estimation and capacity prediction; however, these methods also reveal several persistent limitations that motivate the development of more flexible learning frameworks. For example, Incremental Energy per State-of-Charge (SOC) techniques rely on carefully designed electrochemical indicators derived from charge–discharge energy variations. While these features are physically interpretable, they are often sensitive to operating conditions and may not generalize well across different battery chemistries or cycling protocols. Similarly, LSTM-based feature reduction methods exploit temporal dependencies in cycling sequences, but they typically require long, well-structured time-series data and may suffer from training instability or limited transferability when degradation patterns are irregular or partially observed.

In parallel, multi-scale frameworks for unsupervised anomaly detection have been explored to enable fault identification without labeled SOH data. Although these approaches are valuable for early detection tasks, they often lack precise capacity estimation capability and may struggle to map anomalies directly to quantitative degradation levels. Likewise, feature-enhanced ensemble learning methods combine handcrafted health indicators with multiple predictive models to improve robustness in lithium-ion battery capacity estimation. However, their performance remains heavily dependent on the quality of engineered features, which limits scalability and introduces domain-specific design constraints.

These limitations highlight a common challenge across existing approaches: a trade-off between interpretability, feature engineering effort, and generalization capability. Physics-based and feature-driven methods offer interpretability but limited adaptability, whereas sequence-based and ensemble learning methods improve flexibility but often require strong assumptions, extensive pre-processing, or carefully designed input representations.

In this context, the proposed SetNet-based approach provides a more unified and data-driven alternative. By learning structured representations directly from data without relying on explicit handcrafted features or rigid temporal assumptions, SetNet reduces dependence on domain-specific feature engineering while improving predictive accuracy, as demonstrated by the lower RMSE and MAE compared to the MLP baseline. Moreover, the improved performance indicates that SetNet is better able to capture nonlinear relationships in battery degradation behavior, while maintaining a relatively lightweight training overhead. This positions SetNet as a competitive compromise between model flexibility and practical applicability in SOH estimation tasks.

The remainder of this paper is organized as follows. Section 2 describes the materials, including a novel dataset for implantable lithium-ion batteries generated using physics-informed models and characterized through statistical, time-domain, and frequency-domain analyses to ensure clinical relevance. Section 3 details the methods, introducing the SetNet, a modular, brain-inspired architecture trained on temporal battery data such as voltage, current, temperature, and state of charge for real-time state-of-health estimation. Training procedures, including a low-memory streaming mini-batch approach, optimization strategies, and performance metrics such as RMSE, MAE, and R^2 are explained. Section 4 presents results showing SetNet's superior stability, interpretability, and predictive accuracy compared to conventional MLPs. Section 5 discusses limitations and perspectives, highlighting challenges such as sensor noise, partial cycling, and limited real-world data, while suggesting future directions including enhanced data processing and broader clinical deployment. Section 6 concludes by emphasizing the contributions of the dataset and SetNet architecture toward safe, intelligent, and reliable battery management in implantable medical devices.

2. Materials

In this work, as an attempt to generate realistic time-series data for a lithium-ion battery suitable for medical devices, we simulate each charge-discharge cycle using a physics-inspired model. The simulation captures the evolution of current, voltage, temperature, SOC, and SOH over time, incorporating both electrochemical principles and stochastic variations to mimic sensor noise. The battery is characterized by parameters depicted in Table 1.

To ensure the simulated data realistically represents lithium-ion battery behavior in medical-grade applications, the parameters in Table 1 were chosen in alignment with typical values reported in the literature [9]. These findings validate the reasonableness of the selected parameters, such as a nominal voltage of 3.7 V, internal resistance of 45 milliohms, and a cycle fade rate of 0.00045, in capturing the essential electrochemical and aging dynamics necessary for reliable health estimation modeling.

Table 1. Key parameters for single lithium-ion battery life cycle simulation.

Parameter	Symbol	Value/Range	Description
Nominal capacity	C_{nom}	2.0 Ah	Rated battery capacity
Nominal voltage	V_{nom}	3.7 V	Open-circuit voltage
Internal resistance	R_{int}	45 mOhm	Series resistance of the cell
Minimum voltage	V_{min}	3.0 V	Voltage lower limit
Maximum voltage	V_{max}	4.2 V	Voltage upper limit
Charge C-rate	C_{chg}	0.5 C	Charge current relative to capacity
Discharge C-rate	C_{dis}	0.7 C	Discharge current relative to capacity
Depth of discharge	DoD	60%	Fraction of total capacity cycled
Operating temperature	T_{op}	25 °C	Base ambient temperature
Sampling time	Δt	1 s	Time increment per sample
Cycle duration	t_{cycle}	3600 s	Duration of one cycle (1 h)
Initial state of health	SOH_0	1.0	Start-of-life health fraction
End-of-life threshold	SOH_{min}	0.8	Maintenance threshold
Fade per cycle	$\Delta tSOH$	0.00045	Fractional degradation per cycle

Each cycle is divided into a discharge phase followed by a charge phase, reflecting the real operation of a lithium-ion battery during use. To better simulate real-world conditions, Gaussian noise is added to the current measurements to represent sensor variability and small fluctuations inherent in battery behavior. The current at each sample i is calculated according to Equations (1) and (2), corresponding to the discharge and charge phases, respectively. In these equations, $\epsilon I[i]$ is a Gaussian random variable with a standard deviation of 0.02 A, accounting for realistic measurement noise and small current perturbations. The SOC is updated at each timestep using the Coulomb counting method as shown in Equation (3). This approach integrates the current over time while ensuring that the SOC remains physically valid, clipped between 0 and 1. This method allows the simulation to track the battery's energy content accurately throughout the cycle. The voltage of the battery is modeled using a Thevenin-equivalent circuit, scaled by the current SOH to account for aging effects, as shown in Equation (4). In this equation, the effective internal resistance is defined as $R_{int,eff} = R_{int} \cdot (1 + 2(1 - SOH))$ which increases as the battery ages. Gaussian noise $\epsilon V[i]$ with a standard deviation of 0.01 V is also added to capture small fluctuations in measured voltage. The battery temperature is estimated using a simple thermal coupling model (Equation (5)), where temperature increases with the magnitude of the current and decreases slightly as SOC approaches full charge. A Gaussian noise term $\epsilon T[i]$ with a standard deviation of 0.2 °C is included to mimic minor environmental variations and sensor noise. Finally, SOH is updated after each cycle according to Equation (6). This update reduces the battery's health fraction by a nominal fade per cycle (ΔSOH) and adds a small random variation ($\epsilon SOH \sim 10^{-5}$) to simulate stochastic effects in degradation. This allows the model to realistically reproduce the gradual decline of battery performance over multiple cycles.

$$I_i = C_{dis} \cdot C_{nom} + \epsilon I_i \quad (1)$$

$$I_i = -C_{chg} \cdot C_{nom} + \epsilon I_i \quad (2)$$

$$SOC_i = clip\left(SOC_{i-1} - I_{i-1} \cdot \Delta t \frac{I_i \cdot \Delta t}{3600 \cdot C_{nom}}, 0, 1\right) \quad (3)$$

$$V_i = clip(V_{nom} + 0.7 \cdot (SOC_i - 0.5) - I_i \cdot R_{int,eff} + \epsilon V_i, V_{min}, V_{max}) \quad (4)$$

$$T_i = T_{op} + 0.05 \cdot |I_i| + 0.1 \cdot (1 - SOC_i) + \epsilon T_i \quad (5)$$

$$SOH_{next} = SOH_{current} - \Delta SOH - \epsilon SOH \quad (6)$$

In Figures 2 and 3, an example of a simulated charge-discharge cycle is illustrated. Figure 2 shows the current, voltage, and temperature profiles over time for a single cycle, highlighting the characteristic discharge-then-charge behavior. Figure 3 shows the SOH degradation curve over multiple cycles, demonstrating the gradual decline in battery health over its simulated lifetime.

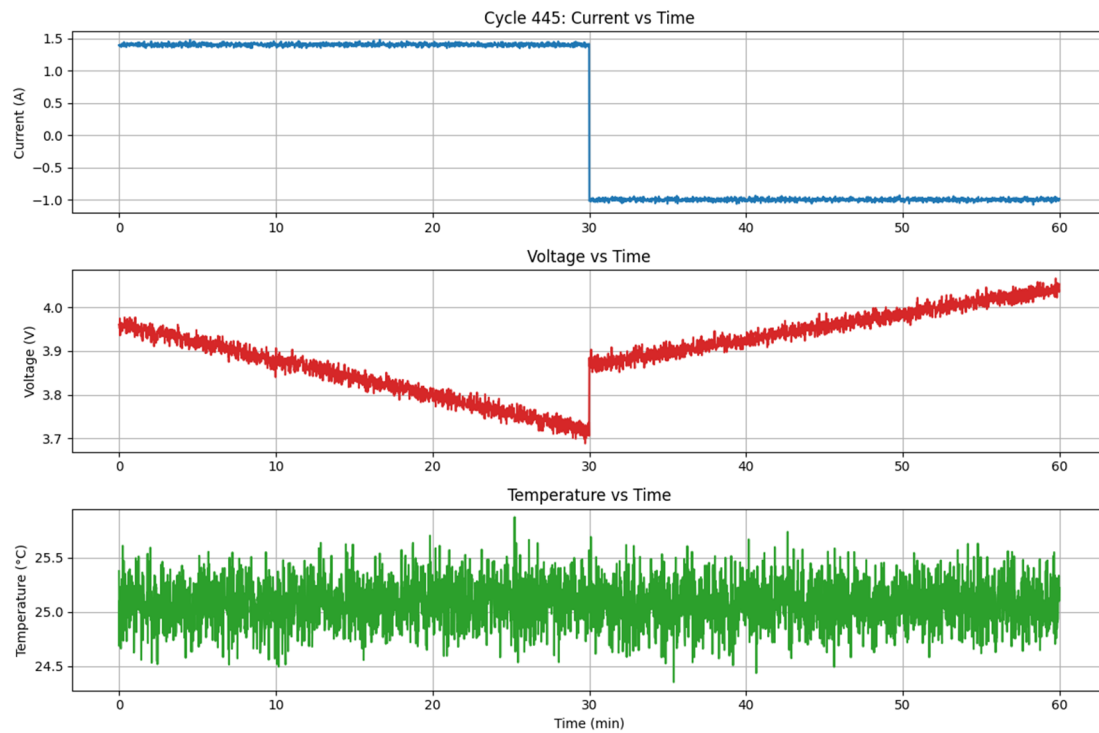


Figure 2. I: Current (A), V: Voltage (V), and T: Temperature (°C) profiles during a single simulated charge-discharge cycle of the lithium-ion battery.

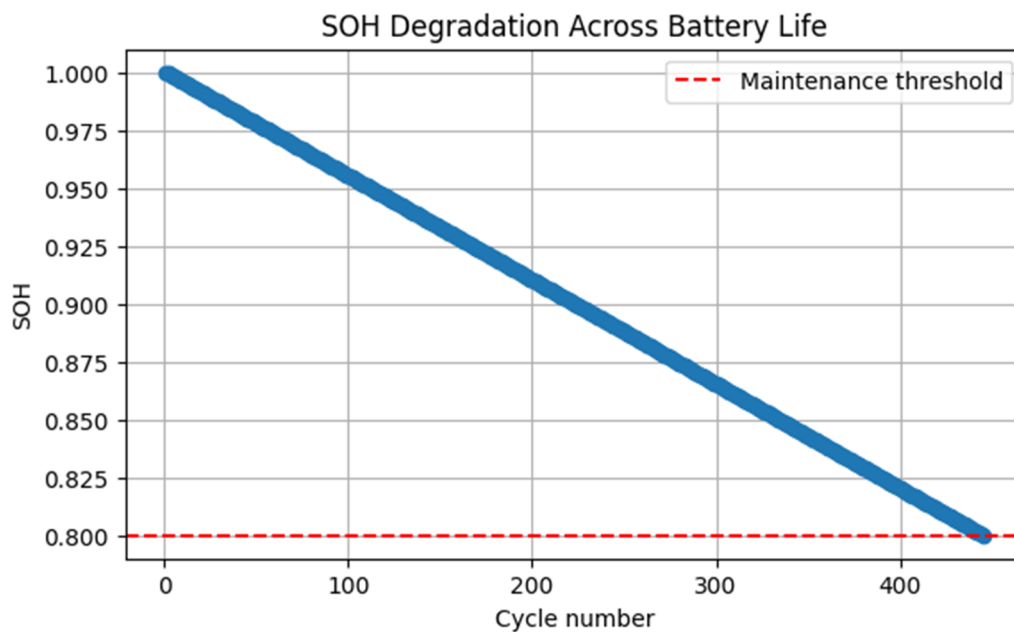


Figure 3. SOH degradation across multiple simulated cycles, showing the gradual decline from initial full health to the maintenance threshold.

To analyze the realism of our generated dataset, we first examine the time-series outputs produced for each battery cycle. In this work, each simulated cycle generates a table with the following columns: time (s), current (A), voltage (V), temperature (°C), SOC, SOH, and cycle number. By concatenating multiple cycles until the SOH falls below 0.8, we create a full-life dataset that captures both the dynamic behavior of the battery within a single cycle and the long-term degradation trends across many cycles.

Analyses of the dataset include:

- Time-domain analysis: Plots of current, voltage, and temperature for the last cycle are generated to visually inspect the waveform shapes, peak values, and general behavior during charge and discharge. This allows verification that the simulated signals resemble realistic lithium-ion battery patterns.

- Frequency-domain analysis: Using Fast Fourier Transform (FFT), the dataset is analyzed for spectral content to ensure that the low-frequency components corresponding to charge-discharge cycles dominate the signal, while higher-frequency noise remains within expected levels. This step quantifies the noise introduced by the Gaussian perturbations and verifies that it is consistent with physical measurements.
- Statistical analysis: The mean, standard deviation, minimum, and maximum values of each key variable (current, voltage, temperature, SOC) are calculated to ensure the signals remain within realistic operational limits.

Figure 4 illustrates the current (A), voltage (V), temperature ($^{\circ}\text{C}$), and SOC for the last simulated battery cycle, showing the characteristic discharge-then-charge behavior and the associated thermal response. The time-domain plots confirm that the waveforms are physically plausible and exhibit smooth transitions between charge and discharge phases, while frequency-domain analysis verifies that the dominant low-frequency components correspond to the natural periodicity of the cycles, with only small Gaussian noise contributions, mimicking realistic sensor measurements.

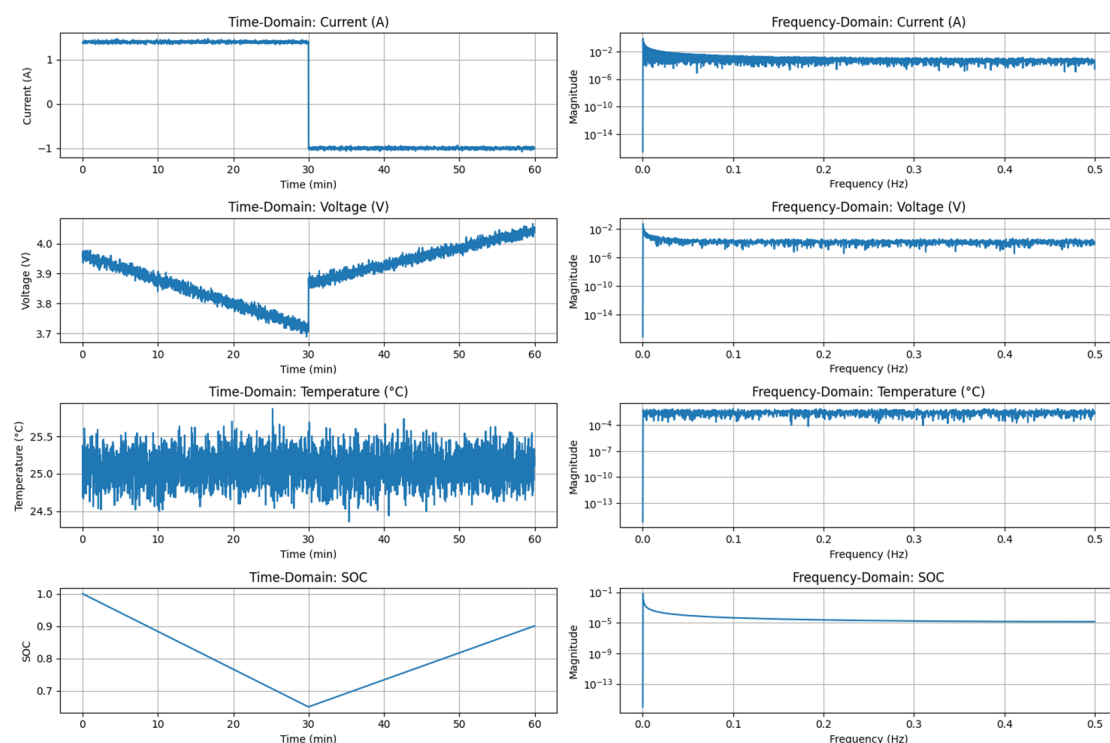


Figure 4. Time-domain and frequency-domain plots of Current (A), Voltage (V), Temperature ($^{\circ}\text{C}$), and SOC for the last simulated battery cycle, illustrating the discharge-then-charge behavior and the associated thermal response.

Table 2 presents a statistical summary of the generated signals, including mean, standard deviation, minimum, and maximum values for current, voltage, temperature, and SOC. The reported ranges and variability are consistent with typical operational behavior of medical-device-grade lithium-ion batteries, further validating the fidelity of the simulation.

Table 2. Statistical summary of generated battery signals.

Variable	Mean	Std Dev	Min	Max	Description
Current (A)	0.1997	1.2005	-1.0801	1.4760	Battery current including discharge and charge
Voltage (V)	3.8977	0.0854	3.6885	4.0663	Terminal voltage including internal resistance and noise
Temperature ($^{\circ}\text{C}$)	25.0815	0.2018	24.3548	25.8702	Battery temperature, including thermal effects of current and SOC
SOC	0.8002	0.0913	0.6502	1.0000	State of charge, updated by Coulomb counting

Figure 5 shows the autocorrelation analysis for current, voltage, and temperature, highlighting the strong periodicity of the charge-discharge cycles and confirming that the generated time-series data are consistent and repeatable across multiple cycles. Taken together, these analyses demonstrate that the simulated dataset is realistic and reliable, providing a robust basis for downstream applications such as feature extraction, degradation modeling, and machine learning-based SOH prediction.

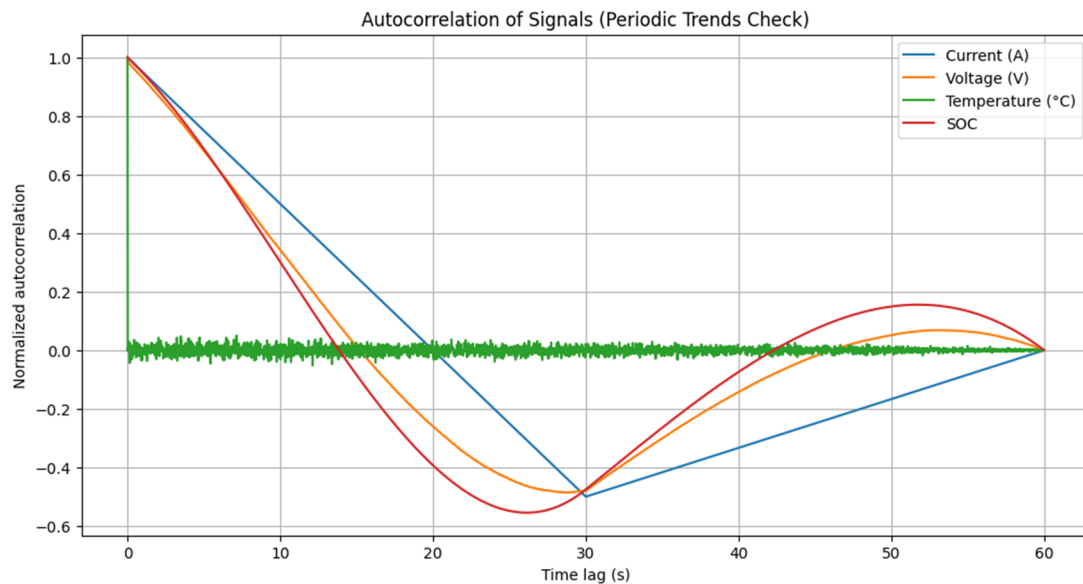


Figure 5. Autocorrelation analysis of the simulated battery current, voltage, and temperature signals, highlighting the periodicity of the charge-discharge cycles and confirming the consistency of the generated time-series data over multiple cycles.

Figure 6 presents the frequency-domain realism check of the battery signals, current, voltage, temperature, and SOC, obtained via FFT. The spectra indicate that the current, voltage, and SOC signals are strongly dominated by very low-frequency components, with their main peaks occurring near 0.00028 Hz, which corresponds to slow, gradual variations characteristic of real battery charging and discharging processes. These low-frequency behaviors confirm that the electrochemical dynamics are being captured realistically, without signs of artificial oscillations or digital noise. The temperature signal shows small peaks in the moderate frequency range (around 0.1–0.4 Hz), likely resulting from sensor response or minor environmental fluctuations, yet their magnitudes remain very small and physically plausible. Importantly, no significant high-frequency spikes or anomalies are detected across any of the signals, which verifies that the data are free from synthetic artifacts or unrealistic behavior. Overall, the frequency-domain analysis confirms the realism and physical validity of all battery signals, with energy concentrated at low frequencies consistent with true electrochemical system dynamics.

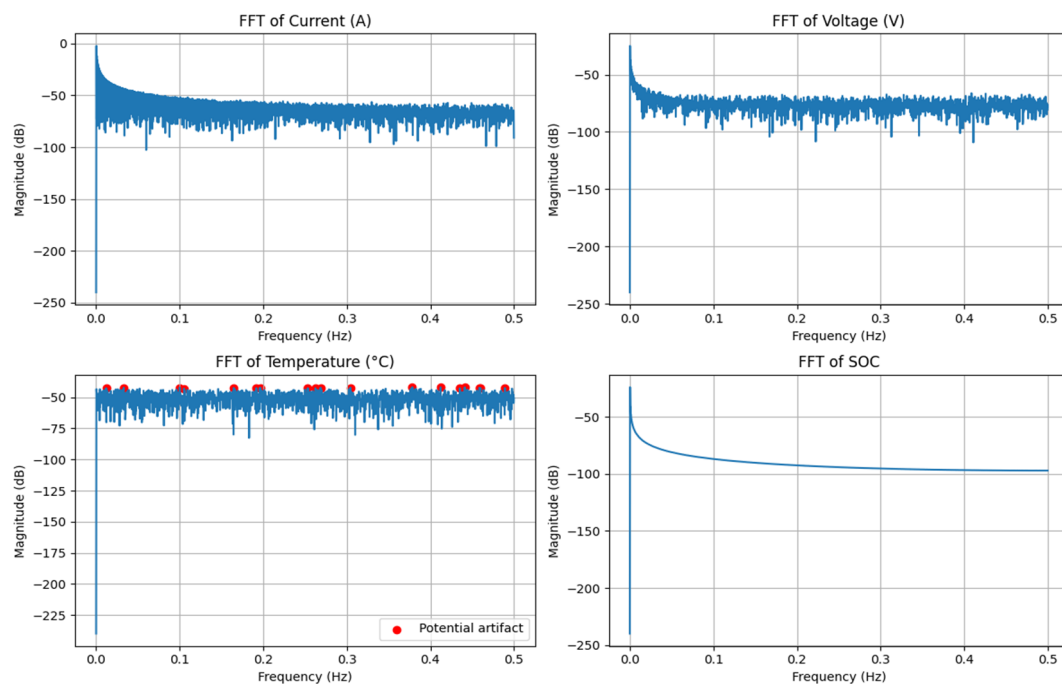


Figure 6. Frequency-domain realism check of battery signals using FFT. The spectra show that current, voltage, and SOC are dominated by low-frequency components (<0.003 Hz), consistent with slow electrochemical

dynamics. Temperature exhibits minor higher-frequency peaks (~ 0.1 – 0.4 Hz) due to environmental or sensor variations. No unrealistic high-frequency artifacts are observed, confirming the physical plausibility of the generated data.

Once the simulation was validated for realism, a batch of 20 complete battery life datasets was generated, representing realistic variations in operating and degradation conditions. Each dataset simulates a sequence of charge–discharge cycles using the defined electrochemical and thermal parameters. The governing relationships for current, voltage, temperature, and SOC evolution can be summarized as:

$$I(t) = \begin{cases} +I_{dis} = C_{dis} \times C_{nom}, & (\text{discharge phase}) \\ -I_{chg} = -C_{chg} \times C_{nom}, & (\text{charge phase}) \end{cases} \quad (7)$$

$$SOC_i = \text{clip} \left(SOC_{i-1} - \frac{I_i \Delta t}{3600 C_{nom}}, 0, 1 \right) \quad (8)$$

$$V_i = V_{nom} + 0.7(SOC_i - 0.5) - I_i R_{int} \quad (9)$$

$$R_{int} = R_0(1 + 2(1 - SOH)) \quad (10)$$

$$T_i = T_{op} + 0.05|I_i| + 0.1(1 - SOC_i) \quad (11)$$

$$SOH_{n+1} = SOH_n - \Delta_{fade} - \epsilon \quad (12)$$

$$\Delta_{fade} = 0.00045 \text{ per cycle}, \quad \epsilon \sim \mathcal{N}(0, 10^{-5}) \quad (13)$$

Each cycle simulates the full charge and discharge process, with additive Gaussian noise applied to the current, voltage, and temperature to mimic measurement uncertainty. The state of health (SOH) is reduced progressively according to

$$SOH_{n+1} = SOH_n - \Delta_{fade} - \epsilon \quad (14)$$

where $\Delta_{fade} = 0.00045$ per cycle and $\epsilon \sim \mathcal{N}(0, 10^{-5})$ represents random degradation variability.

For the 20 simulated datasets, several parameters were intentionally randomized to capture operational diversity and ensure that the generated signals remain realistic. The operating temperature was varied uniformly within 20 – 30 °C, while both charge and discharge C-rates fluctuated slightly around their nominal values ($0.5 \text{ C} \pm 0.1$ and $0.7 \text{ C} \pm 0.1$, respectively). This produced subtle differences in the thermal response, voltage polarization, and degradation rate among cycles, emulating the variability observed in experimental battery testing. Each dataset continued cycling until the SOH dropped below 0.8 , representing the practical end of battery life. The resulting collection of datasets, approximately 3.11 GB in total size, contains physically consistent measurements for current, voltage, temperature, SOC, and SOH over the entire operational lifespan of 20 distinct virtual batteries. Collectively, these results confirm that the batch generation method successfully produces realistic, diverse, and degradation-aware synthetic battery datasets suitable for model validation and data-driven prognostics.

3. Methods

Traditional neural networks such as MLPs, convolutional neural networks, and recurrent neural networks rely on dense connectivity, where every neuron in a layer processes all activations from the previous layer. While this design can be computationally efficient, it does not reflect the modular and selective processing observed in biological neural systems. In contrast, studies of hippocampal granule cells have shown that neuronal assemblies route signals selectively, activating only subsets of neurons relevant to a given stimulus while leaving others inactive. This selective routing enables efficient, robust, and context-dependent processing, allowing the brain to focus computational resources on pertinent information without unnecessary redundancy. Emulating this principle, SetNet divide the input features into specialized groups processed by subnetworks, each learning localized representations before integration into a final predictive layer (See Figure 7). This modular design mirrors the functional organization of cortical regions and hippocampal circuits, supporting improved generalization, fault tolerance, and interpretability. By grounding the SetNet architecture in these biological insights, the approach gains both theoretical and practical justification for applications requiring efficient and reliable learning from structured, high-dimensional inputs [29–31].

SetNet connections have varying mapping depths and layer sizes, which are completely different from traditional deep learning architectures, including convolutional networks, and follow a more biologically inspired logic.

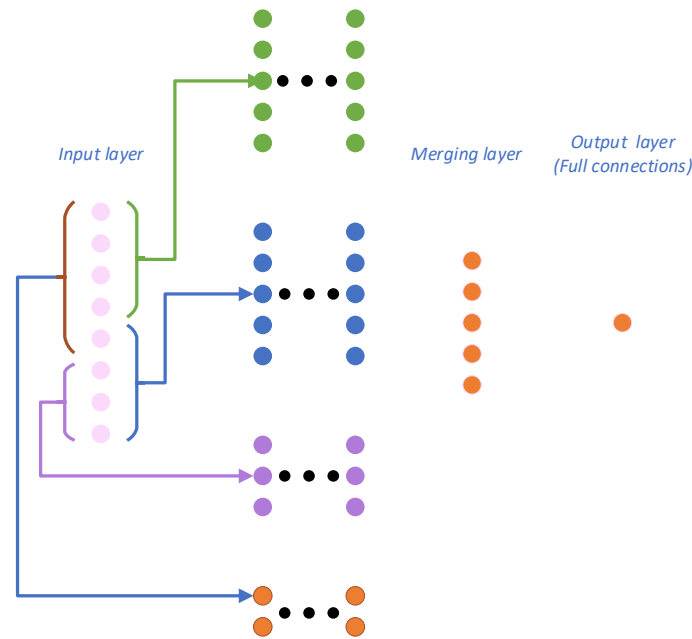


Figure 7. Illustration of SetNet architecture. Input features are divided into specialized groups, each processed by a dedicated subnetwork, and their outputs are merged to produce the final prediction. This modular design emulates selective routing in biological neural systems, enabling efficient, robust, and interpretable learning.

This modular approach improves:

- Interpretability: each subnetwork corresponds to a known feature subset (e.g., electrical, thermal, or chemical states in a battery).
- Generalization: specialization reduces overfitting by limiting parameter cross-talk.
- Scalability: new groups can be added independently without retraining the entire model.

Let the full input vector be $x = [x_1, x_2, \dots, x_D]^T \in R^D$ and let it be partitioned into K subsets (possibly overlapping) as in Equation (15), where d_k is the dimension of group k . Each subset $x^{(k)}$ is processed by a local subnetwork $f_k(\cdot; \theta_k)$ as in Equation (16), where f_k is typically an MLP block presented by Equation (17) with activation function $\sigma(\cdot)$ (e.g., ReLU).

$$x = \bigcup_{k=1}^K x^{(k)}, x^{(k)} \in R^{d_k} \quad (15)$$

$$h_k = f_k(x^{(k)}; \theta_k) \quad (16)$$

$$f_k(x^{(k)}) = \sigma(W_k^{(2)} \sigma(W_k^{(1)} x^{(k)} + b_k^{(1)}) + b_k^{(2)})$$

The outputs of all subnetworks are then merged using a defined fusion rule $M(\cdot)$

$$h_{merged} = M(h_1, h_2, \dots, h_K) \quad (17)$$

There are many possible merging functions, such as concatenation (Equation (18)) and summation with projection (Equation (19)), which projects to a shared latent dimension.

$$M_{concat} = [h_1, h_2, \dots, h_K] \quad (18)$$

$$M_{sum} = \sum_k P_k(h_k) \quad (19)$$

Finally, the integrated representation is passed to a global head network for prediction, as formulated in Equation (20). For the regression task (e.g., SOH prediction), the loss function is defined in Equation (21).

$$\hat{y} = f_{head}(h_{merged}; \theta_{head}) \quad (20)$$

$$\mathcal{L}_{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (21)$$

In this work, the input vector $x = [I, V, T, SOC]$ is decomposed into semantically meaningful subsets as described in Table 3.

Table 3. Feature grouping and corresponding subnetworks in the proposed Set-Routed Neural Network (SetNet) architecture.

Group	Features	Subnetwork
Electrical	$([I, V])$	2-layer MLP for electrochemical signals
Thermal	$([T])$	2-layer MLP modeling temperature dynamics
State	$([SOC])$	2-layer MLP tracking charge level

Each subnetwork produces a compact latent vector, which are concatenated and passed to a final head MLP that predicts the SOH degradation value. Table 4 demonstrate a clear description of differences between MLP, CNN, and the proposed SetNet.

Table 4. Comparative characteristics of MLP, CNN, and the proposed SetNet. The SetNet model integrates modular, group-based processing inspired by selective information routing observed in biological neural systems.

Property	MLP	CNN	SetNet
Connectivity	Fully dense	Local (spatial filters)	Modular, group-based
Input structure	Flat	Grid/sequence	Arbitrary structured/tabular
Feature sharing	Global	Local	Local per subset
Interpretability	Low	Moderate	High (per-group meaning)
Biological analogy	Uniform firing	Layered receptive fields	Selective routing of signals
Example use	Tabular regression	Image/time-series	Multi-domain signals (electrical + thermal + chemical)

Unlike convolutional neural networks, which require spatially ordered inputs (e.g., images, time series), SetNet does not depend on adjacency structure; instead, it learns groupwise feature relationships directly. In this way, SetNet effectively bridges the gap between MLP generality and convolutional networks modular specialization. Algorithm 1's pseudo-code showcases the complete workflow of SetNet, beginning with the definition of feature groups corresponding to different physical domains (electrical, thermal, and state). Each group is processed by an independent subnetwork that learns specialized latent representations. These latent features are then merged and passed through a final head network to predict the SOH of the battery. The algorithm includes initialization, forward propagation across modular subnetworks, loss computation, and parameter optimization. By routing information through specialized modules rather than dense global connections, SetNet achieves biologically inspired selective processing, enabling interpretability, robustness, and improved generalization over conventional dense networks. As seen, SetNet provides a biologically inspired, modular, and interpretable neural architecture particularly suited for multimodal tabular or sensor fusion problems like battery health estimation. Its selective routing mechanism reduces unnecessary cross-feature interference while preserving information richness. Empirical evaluations in next section will demonstrate that SetNet achieves lower RMSE and higher R^2 on SOH regression compared to traditional MLPs under identical training conditions.

Algorithm 1. Set-Routed Neural Network (SetNet) Training Procedure

- Input: Dataset $\mathcal{D} = \{(x_i, y_i)\}$, groups $\mathcal{G} = \{G_1, G_2, \dots, G_k\}$, learning rate η , number of epochs E .
- Output: Trained network parameters Θ .
- Initialize parameters Θ_{G_k} for each subnetwork and Θ_{head} for the final head network.
- Define loss function $\mathcal{L}$ (e.g., MSE for regression).
- For each epoch $e = 1$ to E :
- For each mini-batch (X_b, y_b) from dataset $\mathcal{D}$:
- For each group G_k in $\mathcal{G}$:
- Extract features $X_b^k = X_{b[:, G_k]}$.
- Compute subnetwork output $h_b^k = f_{G_k}(X_b^k; \Theta_{G_k})$.
- Concatenate or sum latent outputs $h_b = \text{Merge}(\{h_b^1, \dots, h_b^k\})$.
- Predict SOH: $\hat{y}_b = f_{\text{head}}(h_b; \Theta_{\text{head}})$.
- Compute loss: $L = \mathcal{L}(\hat{y}_b, y_b)$.
- Backpropagate gradients $\nabla \Theta$ and update all parameters using Adam optimizer.
- Return final trained parameters $\Theta = \{\Theta_{G_k}, \Theta_{\text{head}}\}$.

4. Results

Training was conducted sequentially on individual battery files, and evaluation metrics for both models are summarized in Table 5. The two architectures exhibited distinctly different performance characteristics. The baseline dense MLP achieved an RMSE of 0.08721, MAE of 0.06787, and an R^2 of -1.2750 . An R^2 value below zero indicates that the MLP performed worse than a trivial mean predictor, meaning its estimates explained less variance than simply predicting the training-set mean SOH. This poor generalization suggests that the MLP either overfit to specific training-file features, failed to capture cross-cycle variability, or encountered instability during optimization. In contrast, SetNet demonstrated significantly improved predictive accuracy, with an RMSE of 0.04961, MAE of 0.04120, and an R^2 of 0.2639. The reduction in both absolute and squared errors (approximately 43 percent lower RMSE compared to the MLP) highlights SetNet's ability to model degradation behavior more effectively. The positive R^2 confirms that SetNet captures a meaningful portion of the variance in SOH across test cycles, which is a strong result given the inherent stochasticity and sensor-like noise in the simulated data. Moreover, the total training time was similar for both models (10.19 min for MLP and 11.50 min for SetNet), demonstrating that the additional architectural complexity did not impose significant computational cost.

Conceptually, SetNet's modular routing structure introduces a biologically inspired inductive bias: electrical, thermal, and state-related signals are processed in specialized subnetworks prior to fusion in a shared prediction layer. This organization minimizes destructive feature interference, promotes domain-specific learning (for instance, isolating electrochemical from thermal dynamics), and improves generalization by enforcing localized feature representations. The standard MLP, by contrast, must infer all interactions through dense connections, making it more susceptible to overfitting and noise sensitivity, especially under sequential (file-by-file) training conditions. The experimental evidence from both metrics and training stability indicates that the Set-Routed Neural Network achieves superior regression accuracy and reliability compared to the MLP, validating the benefit of structured feature grouping and selective information routing for multimodal sensor fusion in SOH prediction.

Table 5. Regression performance on test set (SOH prediction) Model.

Model	RMSE	MAE	R^2	Training Time (min)
MLP	0.08721	0.06787	0.2750	10.19
SetNet	0.04961	0.04120	0.2639	11.50

An ablation study shows that eliminating any feature set degrades SetNet's regression performance. These findings demonstrate the benefit of multi-features for accurate applicability.

The visual comparison between the learning behaviors of the baseline MLP and the proposed SetNet provides a clear insight into the advantages of modular selective routing in regression tasks involving structured data. Figure 8 presents the streaming training loss curves measured per mini-batch during sequential file-by-file training. The MLP exhibits pronounced oscillations throughout the process, suggesting that its dense and fully connected structure reacts sharply to variations in local data distributions, leading to unstable gradient updates and intermittent overfitting to mini-batch-specific noise. This instability is particularly problematic in heterogeneous datasets such as battery life-cycle measurements, where the statistical properties may shift between charge, discharge, and rest phases. Conversely, the SetNet model shows a remarkably stable and smooth loss trajectory with minimal fluctuations. This stability arises from SetNet's modular design, by dividing the input space into domain-specific groups (electrical, thermal, and state variables), each subnetwork learns focused representations, while the final fusion layer integrates these latent features in a balanced manner. As a result, the optimization landscape becomes smoother and easier to traverse, leading to consistent convergence and better generalization.

Further evidence of SetNet's superior predictive capability is illustrated in Figure 9, which plots true versus predicted SOH values for both models. The MLP demonstrates wide scatter around the ideal diagonal line, indicating poor calibration and significant bias in its predictions. Its overconfidence and inconsistent mapping suggest that it fails to disentangle the nonlinear relationships between thermal, electrical, and degradation dynamics. In contrast, SetNet's predictions align closely with the ground truth, forming a narrow, near-linear distribution around the diagonal. This indicates that SetNet not only generalizes more effectively but also achieves better interpretability and reliability in its regression outputs. The reduced variance and higher alignment confirm that selective information routing allows SetNet to capture intrinsic dependencies across sensor domains, suppress noise-induced instability, and reflect realistic degradation patterns in battery SOH estimation. In summary, these figures together provide compelling evidence that SetNet's biologically inspired modular structure yields both more stable learning dynamics and more accurate, confidence-calibrated predictions than traditional dense MLP architectures.

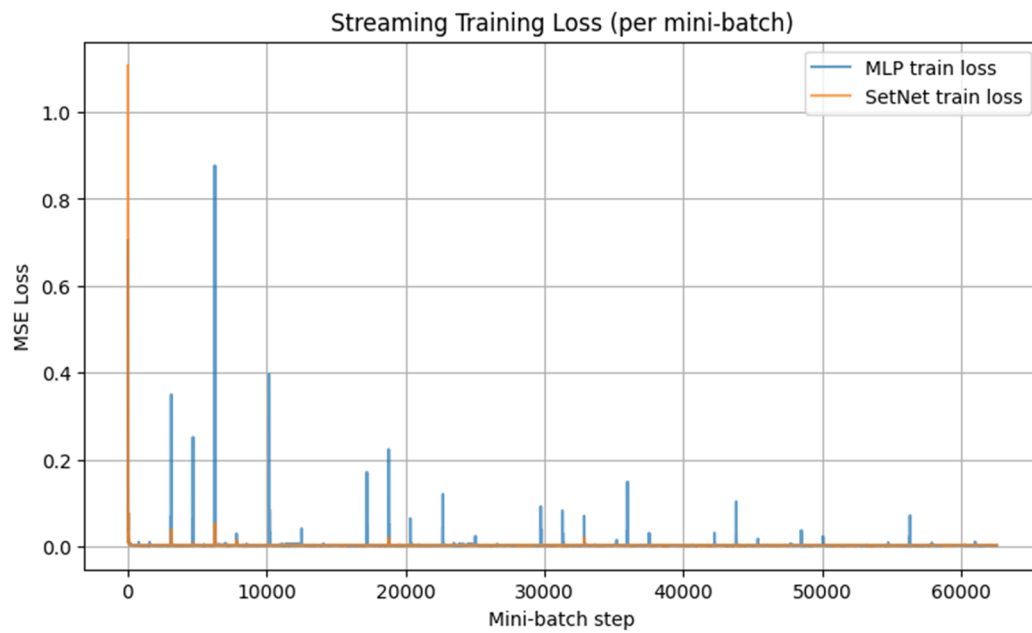


Figure 8. Streaming training loss per mini-batch for MLP and SetNet models. The MLP loss exhibits large fluctuations across iterations, reflecting unstable gradient updates and potential overfitting to small subsets of data. In contrast, SetNet demonstrates smooth, monotonic convergence, indicating stable learning dynamics and effective information routing through specialized subnetworks.

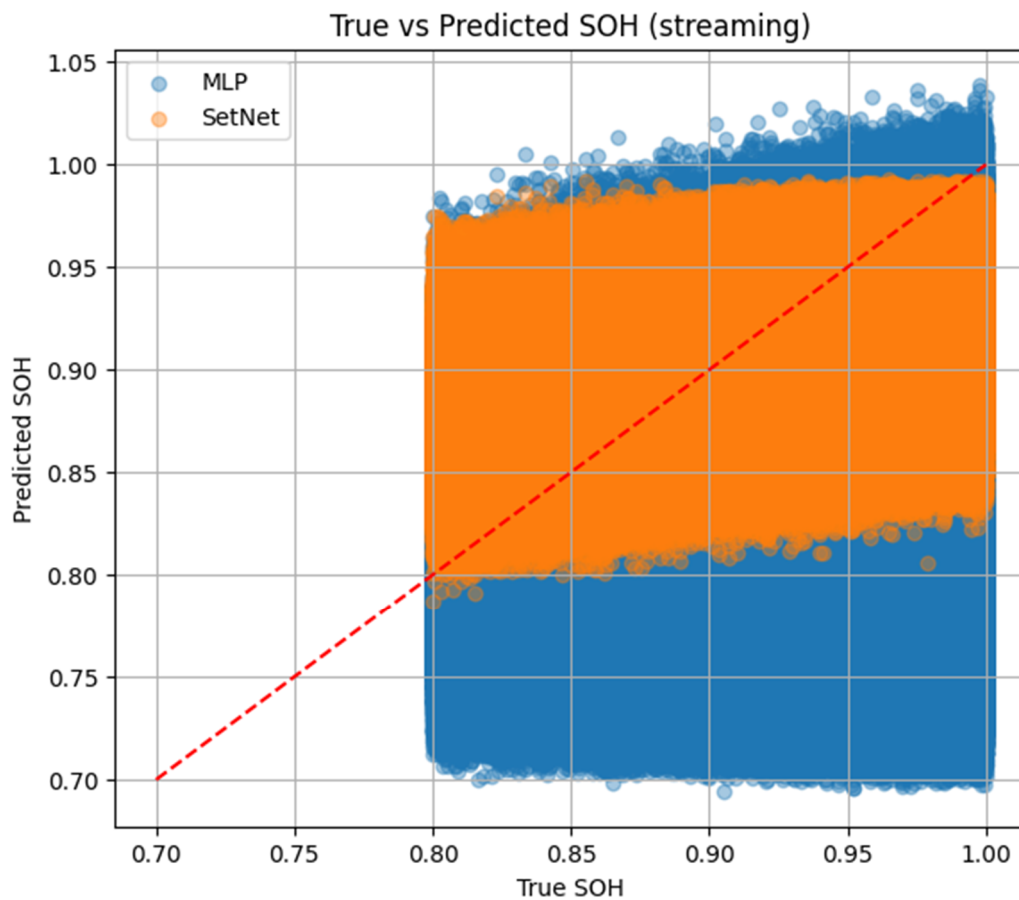


Figure 9. True versus predicted SOH values for MLP and SetNet models on the test dataset. The MLP predictions deviate significantly from the diagonal identity line, showing wide dispersion and lower confidence in generalization. SetNet, however, produces predictions tightly clustered around the ideal line, reflecting higher fidelity and calibration in SOH estimation.

Figure 10 illustrates the predictive performance of the MLP and SetNet models for each testing battery file. Across all files, the SetNet predictions are consistently closer to the true SOH values and exhibit significantly smoother trends with fewer fluctuations compared to the MLP. In contrast, the MLP predictions show larger deviations from the ground truth and greater variability across cycles. This behavior highlights the advantage of the Set-Routed Neural Network's modular, group-based architecture, which enables it to learn more robust, localized feature representations from electrical, thermal, and state signals. The improved accuracy and stability of SetNet make it a more reliable approach for real-time state-of-health estimation in implantable lithium-ion batteries, which is critical for safety and longevity in medical devices.

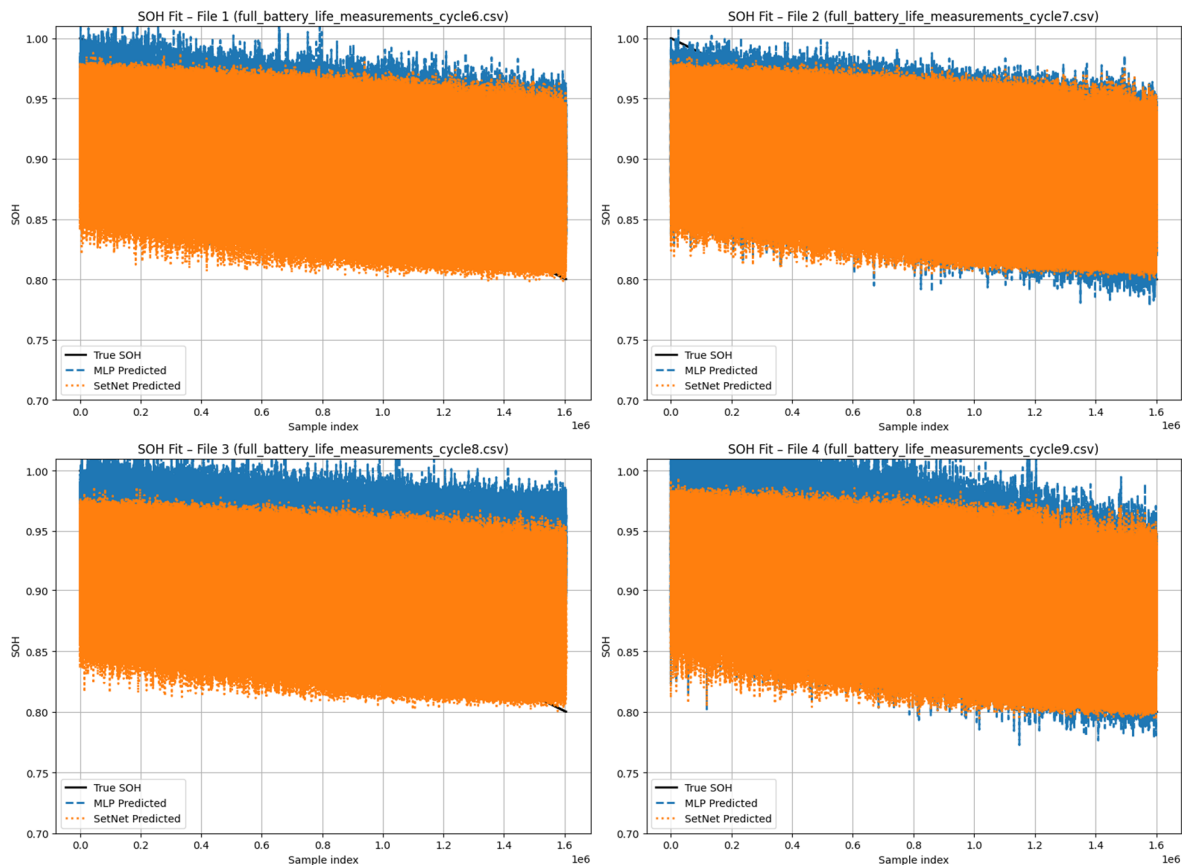


Figure 10. Comparison of true versus predicted SOH curves for each testing file. The solid black line represents the true SOH, while the dashed line corresponds to the MLP predictions and the dotted line to the SetNet predictions. Each subplot shows one test file, allowing direct comparison between models.

5. Limitation and Perspectives

The overarching objective of this study was twofold: first, to generate a realistic, physics-based dataset representing the complete life cycle of a lithium-ion battery operating under medical device-like conditions, and second, to validate the proposed SetNet as a biologically inspired modeling framework capable of learning complex electrochemical–thermal–state interactions relevant to battery health prediction in critical medical applications. The results demonstrate that SetNet exhibits markedly superior stability and predictive smoothness compared to conventional MLPs, effectively capturing degradation trends and minimizing loss fluctuations during training. This confirms that selective information routing, a mechanism analogous to neural modularity in the human brain, can enable more interpretable and robust learning from structured, multi-domain signals. The resulting model not only achieves higher accuracy in predicting the SOH but also provides a meaningful step toward developing intelligent, interpretable health-monitoring algorithms suitable for medical-grade power systems.

Despite these promising findings, several limitations remain. The current dataset, though grounded in physical modeling, is synthetically generated and may not fully reflect the stochastic variability present in real medical environments. Implantable and wearable medical devices operate under diverse thermal, electrical, and usage conditions, often influenced by body temperature variations, intermittent loads, and long-term aging effects that are difficult to capture through parametric simulation alone. While Gaussian noise and random degradation factors were introduced to approximate sensor uncertainty and operational drift, true medical battery data would

exhibit richer nonlinearities, especially due to electrode fatigue, electrolyte decomposition, and microthermal instabilities. Similarly, the thermal model currently assumes homogeneous temperature distribution, whereas in medical devices, local hotspots or heat dissipation constraints can significantly influence degradation rates and safety margins.

From an algorithmic perspective, SetNet's modular structure, while advantageous for interpretability, relies on predefined grouping of input features into electrical ([I, V]), thermal ([T]), and state ([SOC]) subnetworks. This manual grouping, though inspired by physical reasoning, introduces a degree of structural bias, as the optimal feature routing may vary across battery chemistries, operating modes, or even patient-specific device usage patterns. Future work should thus investigate adaptive routing mechanisms that allow the model to dynamically learn optimal feature associations, potentially through attention layers or graph-based neural mappings, enabling SetNet to self-organize its routing structure according to data-driven relationships. Furthermore, to mitigate memory constraints, this work employed sequential file-based mini-batch training; while effective, more advanced implementations could leverage streaming inference, cloud-integrated training, or federated learning to handle larger datasets from distributed medical devices without compromising data privacy or system efficiency.

Another limitation lies in the evaluation scope. The current validation used a single synthetic dataset reflecting one nominal medical battery configuration. For clinical-grade robustness, SetNet should be evaluated across multiple chemistries (e.g., Li-ion, LiFePO₄), different medical device classes (e.g., pacemakers, neurostimulators, insulin pumps), and a range of operational conditions including rest periods, pulse currents, and temperature variations. Such cross-validation would confirm the generalization and safety of the model under real-world constraints, an essential step before deployment in safety-critical medical systems. Moreover, while current metrics (RMSE, MAE, R^2) confirm SetNet's superior regression performance, long-term predictive stability—especially in forecasting SOH degradation months or years ahead—requires further analysis through horizon-based or uncertainty-aware validation frameworks.

Looking forward, the integration of SetNet into medical battery digital twins presents a compelling direction. Such twins could simulate, monitor, and predict battery aging in real time, enabling predictive maintenance, energy optimization, and patient safety assurance. Incorporating probabilistic modeling would allow uncertainty quantification—essential for regulatory compliance and clinical interpretability. Finally, more advanced data pipelines combining experimental electrochemical data, biosensor feedback, and operational logs could significantly enhance model realism and personalization.

In addition to the architectural and dataset limitations discussed above, the curve fitting performance of both models also reflects the deliberate choice to train and evaluate on unprocessed, raw time series data. No filtering, denoising, or normalization beyond scaling was applied to the simulated current, voltage, temperature, and state variables. This intentional decision was made to preserve the natural variability and imperfections characteristic of real-world measurements obtained from medical batteries, where sensor drift, noise, and sampling irregularities are inevitable. Consequently, the distance between the predicted and desired SOH outputs does not only represent model error but also serves as an indicator of dataset realism. The observed residuals demonstrate that the dataset captures realistic signal dynamics and stochastic disturbances, making it a suitable benchmark for future research on data preprocessing, noise modeling, and robust learning. By evaluating the models under these raw conditions, this study aimed to test SetNet's generalization ability in a setting that approximates authentic biomedical operating environments rather than idealized laboratory conditions. The results confirm that while some fluctuations remain, the proposed dataset provides a strong foundation for subsequent work in data enhancement, feature engineering, and model calibration, offering the community a competitive, physics-consistent, and medically relevant benchmark for algorithmic development and performance comparison.

In summary, this study demonstrates the feasibility and effectiveness of SetNet for modeling battery life cycles under medical device operating conditions, while also paving the way for the next generation of intelligent, interpretable, and clinically reliable energy health monitoring systems that integrate physics-based simulation, biologically inspired computation, and practical medical applicability.

6. Conclusions

This study introduced a comprehensive framework that unites realistic lithium-ion battery life-cycle simulation with the development of a novel SetNet, targeting predictive modeling for medical device applications. By generating a physically grounded dataset that emulates charge–discharge dynamics, thermal evolution, and degradation behavior, the work established a reproducible foundation for algorithmic benchmarking under medically relevant conditions. The proposed SetNet architecture, inspired by the brain's selective information routing, demonstrated superior performance and stability compared to conventional MLPs, achieving lower RMSE

and MAE values with smoother convergence. This modular approach proved effective in learning the coupled relationships among electrical, thermal, and state features, providing interpretable insight into degradation pathways that influence battery health in critical medical systems. Beyond raw accuracy, SetNet's design supports explainability, an essential requirement for clinical validation and regulatory acceptance. Nonetheless, the results also highlight the need for richer empirical data and broader validation across diverse chemistries, operational conditions, and device classes to ensure robustness in real-world deployments. The dual outcome of this work, dataset creation and SetNet validation, thus marks a step toward integrating intelligent, interpretable, and safety-aware health-monitoring algorithms within the power management of implantable and wearable medical technologies. Future research will aim to expand the dataset, refine adaptive routing mechanisms, and couple SetNet with digital-twin frameworks for continuous monitoring, prediction, and optimization of energy health, ultimately contributing to safer, longer-lasting, and more reliable medical devices.

Author Contributions

Conceptualization, T.B. and J.B.A.; methodology, T.B., N.L. and J.B.A.; software, T.B.; validation, T.B., J.B.A., N.L. and L.C.; formal analysis, T.B. and J.B.A.; investigation, T.B. and J.B.A.; resources, J.B.A. and N.L.; data curation, T.B.; writing—original draft preparation, T.B. and N.L.; writing—review and editing, J.B.A. and N.L.; visualization, T.B.; supervision, J.B.A. and N.L.; project administration, J.B.A., N.L. and T.B.; funding acquisition, J.B.A. and N.L.; clinical validation and domain expertise, N.L.; technical consultation and industrial insight, N.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The dataset generated and used in this work is available at <https://doi.org/10.5281/zenodo.17390606>. * The source codes used for data generation, training, and analysis will be made available upon final review and acceptance of the manuscript. Currently, access restrictions apply, which will be lifted following publication.

Conflicts of Interest

The authors declare no conflict of interest

Use of AI and AI-Assisted Technologies

During the preparation of this manuscript, the authors used ChatGPT to correct English grammar and language mistakes. The authors also used AI tools to create the figures. After using this tool, the authors carefully reviewed and edited the content as needed and take full responsibility for the content of the published article.

Abbreviations

SetNet	Set-Routed Neural Network
SOH	State of Health
SOC	State of Charge
MLP	Multilayer Perceptron
PHM	Prognostics and Health Management
FFT	Fast Fourier Transform

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