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Review

Recent Progress of Deep Learning Methods for Health Monitoring of Lithium-Ion Batteries

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Abstract: In recent years, the rapid evolution of transportation electrification has been propelled by the widespread adoption of lithium-ion batteries (LIBs) as the primary energy storage solution. The critical need to ensure the safe and efficient operation of these LIBs has positioned battery management systems (BMS) as pivotal components in this landscape. Among the various BMS functions, state and temperature monitoring emerge as paramount for intelligent LIB management. This review focuses on two key aspects of LIB health management: the accurate prediction of the state of health (SOH) and the estimation of remaining useful life (RUL). Achieving precise SOH predictions not only extends the lifespan of LIBs but also offers invaluable insights for optimizing battery usage. Additionally, accurate RUL estimation is essential for efficient battery management and state estimation, especially as the demand for electric vehicles continues to surge. The review highlights the significance of machine learning (ML) techniques in enhancing LIB state predictions while simultaneously reducing computational complexity. By delving into the current state of research in this field, the review aims to elucidate promising future avenues for leveraging ML in the context of LIBs. Notably, it underscores the increasing necessity for advanced RUL prediction techniques and their role in addressing the challenges associated with the burgeoning demand for electric vehicles. This comprehensive review identifies existing challenges and proposes a structured framework to overcome these obstacles, emphasizing the development of machine-learning applications tailored specifically for rechargeable LIBs. The integration of artificial intelligence (AI) technologies in this endeavor is pivotal, as researchers aspire to expedite advancements in battery performance and overcome present limitations associated with LIBs. In adopting a symmetrical approach, ML harmonizes with battery management, contributing significantly to the sustainable progress of transportation electrification. This study provides a concise overview of the literature, offering insights into the current state, future prospects, and challenges in utilizing ML techniques for lithium-ion battery health monitoring.

Keywords: lithium-ion battery; transportation electrification; energy storage; electric vehicle; deep learning; state-of-health; machine learning

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1. Introduction

Energy storage plays a pivotal role in the transition toward a low-carbon, sustainable future. The capacity prediction of lithium-ion batteries (LIBs) is particularly crucial for effective energy storage management in applications ranging from electric vehicles (EVs) to electricity grid management. In recent years, LIBs have experienced widespread adoption across diverse industrial sectors, including automotive (cars and EVs), power tools, and medical devices.

Rechargeable LIBs have swiftly become a leading energy storage solution, especially in the realm of electric vehicle applications. Their appeal lies in a combination of high specific energy, decreasing costs, and acceptable cycle life, contributing significantly to their popularity. However, despite these advantages, accurately predicting the parameters of these intricate and nonlinear battery systems remains a formidable challenge.

This challenge is further compounded by factors such as diverse aging mechanisms, cell-to-cell variations, and dynamic operating conditions, making it imperative to forecast battery performance under realistic scenarios. The intricate nature of LIBs and their sensitivity to various environmental and usage factors underscore the need for precise prediction methods. This becomes especially critical given the increasing significance of battery states and parameters across various application contexts.

In the contemporary landscape, LIBs stand as pivotal energy-storage devices, influencing a wide array of societal applications. In this context, understanding and accurately predicting the behavior of these batteries becomes paramount for ensuring efficient and sustainable energy storage solutions.

Despite the remarkable progress, LIBs still face challenges in terms of performance and cost, particularly concerning energy density, power density, cycle life, safety, and other critical aspects. Traditionally, the enhancement of battery performance has relied on time-consuming "trial-and-error" experiments.

In response to these challenges, computational chemistry, and artificial intelligence (AI) emerge as promising solutions to accelerate research and development efforts toward improved battery systems. This review delves into a diverse spectrum of AI technologies applied to predict and discover battery materials, as well as estimate the state of the battery system.

A notable contribution to this field is the work of Tran et al. [1], who conducted an extensive examination, assessment, categorization, and comparison of adaptable mathematical frameworks related to deep learning algorithms used in predicting the remaining useful life (RUL) of batteries. Their study identified attributes crucial for modeling proficiency and employed them to categorize these adaptable predictive approaches. To evaluate various modeling precisions within the deep learning computation process, rigorous criteria were established. The key aspects of successful life prediction were then used to derive pertinent findings and recommendations. Notably, the study identified the high-precision deep convolutional neural network—extreme learning machine algorithm as particularly effective in ensuring consistent and reliable prediction of the RUL of LIBs. This selection highlights the potential for specific AI algorithms to play a crucial role in advancing the accuracy and reliability of life predictions for battery systems.

To offer a comprehensive understanding of the role of deep learning in the prognostics and health management (PHM) of Li-ion batteries, Mou et al. [2] conducted an insightful overview based on current research. Their work outlines three fundamental stages in the application of deep learning to Li-ion battery PHM: data collection, the implementation of deep learning methods, and performance assessment. The article begins by introducing prevalent data types and relevant publicly available datasets, providing a foundational understanding of the information utilized in Li-ion battery PHM. Subsequently, it succinctly explains various deep learning techniques employed in this field, encompassing auto-encoders, deep neural networks, deep belief networks, convolutional neural networks, recurrent neural networks, and generative adversarial networks (GANs). The review not only details the application of these deep learning techniques but also outlines standard evaluation criteria essential for assessing their efficacy in the context of Li-ion battery PHM. This critical analysis allows for a comprehensive understanding of the strengths and limitations of each technique, aiding researchers, and practitioners in selecting suitable approaches for their specific applications. A concluding statement in the review summarizes the key insights gleaned from the exploration of deep learning in Li-ion battery PHM. Furthermore, the paper discusses the future potential of employing deep learning approaches in this field, providing a forward-looking perspective on the ongoing advancements and opportunities for further research and application.

In a comprehensive examination by Meng et al. [3], prevalent equivalent circuit and electrochemical models, commonly used for predicting battery states, are scrutinized. The review underscores that machine learning and deep learning methodologies stand out as effective contributors to formulating efficient and precise data-derived models for forecasting battery performance. This encompassing analysis delves into the complexities, advantages, and limitations of these methodologies, providing a nuanced understanding of their applications.

Moving forward, Zhang et al. [4] categorize contemporary techniques for estimating the SOC using deep learning into two distinct categories: structured adjustment and unstructured improvement. The article accentuates the dynamic trends in network architecture applications over time. The critical aspects of implementing deep neural network methods are explored, including feature engineering, data augmentation, learning rate strategies, optimization functions, and optimal hyperparameters. The review not only surveys the theory and essential techniques of existing methods but also analyzes the outcomes of these estimation approaches, compactly summarizing their effectiveness. Importantly, the paper concludes by delving into potential directions for future developments in state-of-charge estimation methods specifically tailored for LIBs in EVs. This forward-looking perspective provides valuable insights for researchers and practitioners, guiding the ongoing evolution of methodologies in the dynamic field of battery state estimation.

2. Transformer-Based Models and Variants

2.1. Transformer-Based Models

Han et al. [5] proposed a method to predict the RUL of LIBs using a transformer-based neural network that leverages denoising auto-encoders (DAE) to reduce noise in capacity data, leading to improved prediction accuracy. The denoising transformer network for RUL prediction is illustrated in Figure 1. Hu et al. [6] focused on state-of-health (SOH) prediction using electrochemical impedance spectroscopy (EIS) data. They utilized feature extraction to enhance information from EIS measurements, leading to a substantial reduction in prediction error. Tian et al. [7] introduced a comprehensive approach integrating data pre-processing and a convolutional neural network (CNN) transformer framework for SOH prediction. They achieved high accuracy in SOH estimation by minimizing feature redundancy and normalization. Hu et al. [6] used vision transformer networks (VITs) to predict SOH, focusing on discrete charging data within a predetermined voltage range and incorporating transfer learning principles. Their method showed superior prediction accuracy compared to existing deep learning methods. The algorithm flowchart, transformer structure, and structure of VIT for SOH estimation are illustrated in Figure 2. These advancements signify promising strides in refining SOH prediction methodologies for enhanced battery health management. Fu et al. [8] introduce a method for predicting SOH using discrete charging data and a VIT model. The unique aspect of their approach is the incorporation of transfer learning principles, which involves training the prediction model on source task LIB data and fine-tuning it on target task LIB data. This process enhances prediction precision and tailors the model's capabilities to the specific characteristics of the target LIBs. Their method demonstrates superior prediction accuracy and transfer effects compared to existing deep learning methods. However, this method may also require significant computational resources. Finally, Ye et al. [5] proposed a multi-winding transformer-based cell equalizer for cell equalization, eliminating complex control strategies while maintaining scalability and efficiency. Overall, these methods offer various advantages, such as improved prediction accuracy, reduced computational complexity, enhanced information extraction, and scalable and efficient cell equalization. However, they also have disadvantages like the need for extensive training data, high computational requirements, and limited applicability to specific battery types or conditions. Further research is needed to address these limitations and develop more versatile and effective battery monitoring and management methods. The calculation process for attention weight is illustrated in Figure 3.

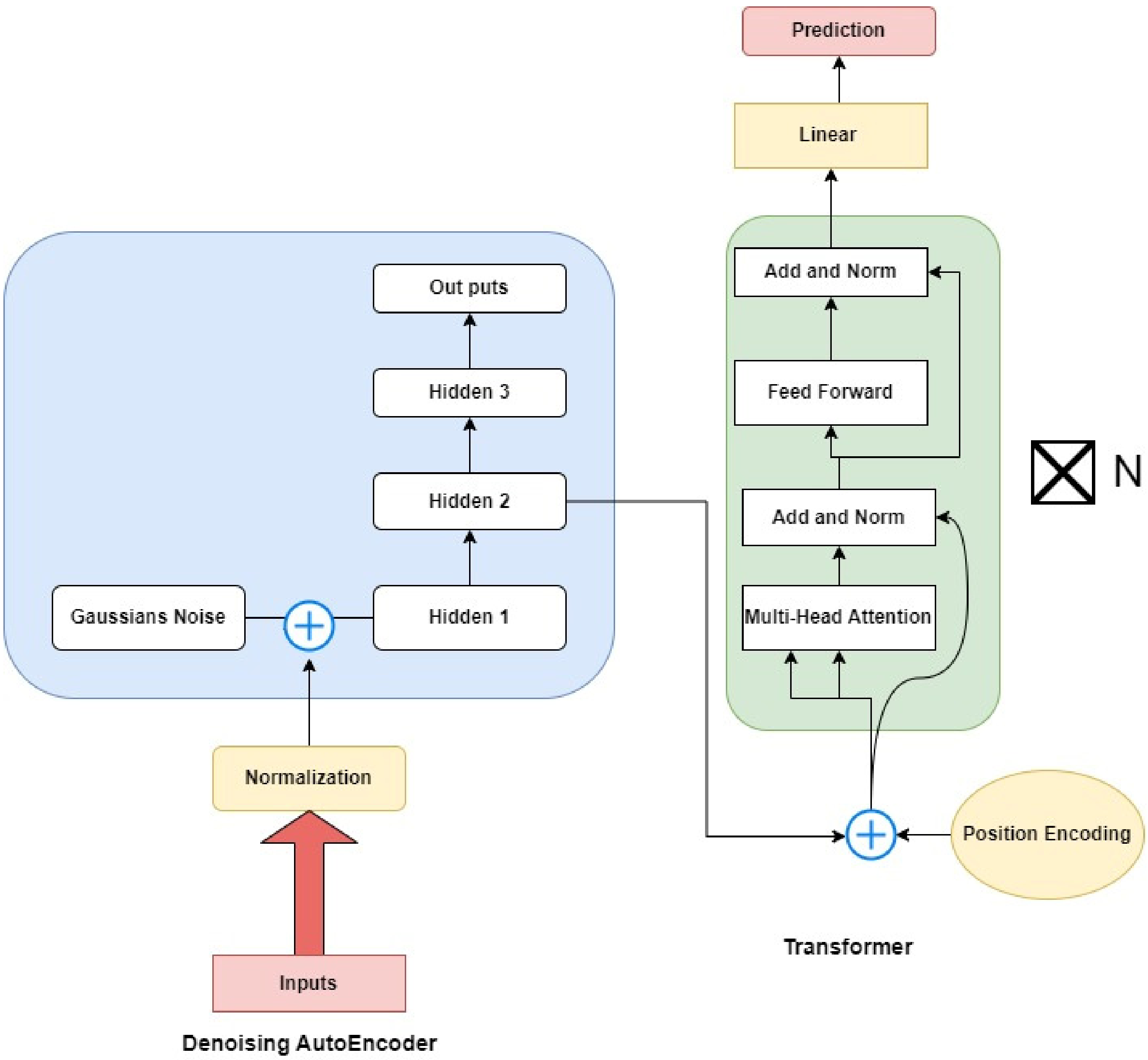

Figure 1. Denoising transformer network for RUL prediction [5].

These methods have their advantages and disadvantages. The transformer-based neural network approach offers high accuracy in RUL prediction but may require extensive data and computational resources. EIS-based methods provide valuable insights but require specialized equipment and complex data collection processes. CNN-Transformer frameworks offer high accuracy but can be computationally intensive. VITs demonstrate superior performance but require significant computational resources. Multi-winding transformer-based cell equalizers simplify equalization but are limited to specific battery configurations. In summary, each method has its own unique advantages and limitations, and the choice depends on factors such as computational resources, data availability, and the specific requirements of the battery monitoring application. Further research is necessary to develop more versatile and efficient battery health management methods. Figure 4. Demonstrate the hyperparameters of self-attention transformer model [8].

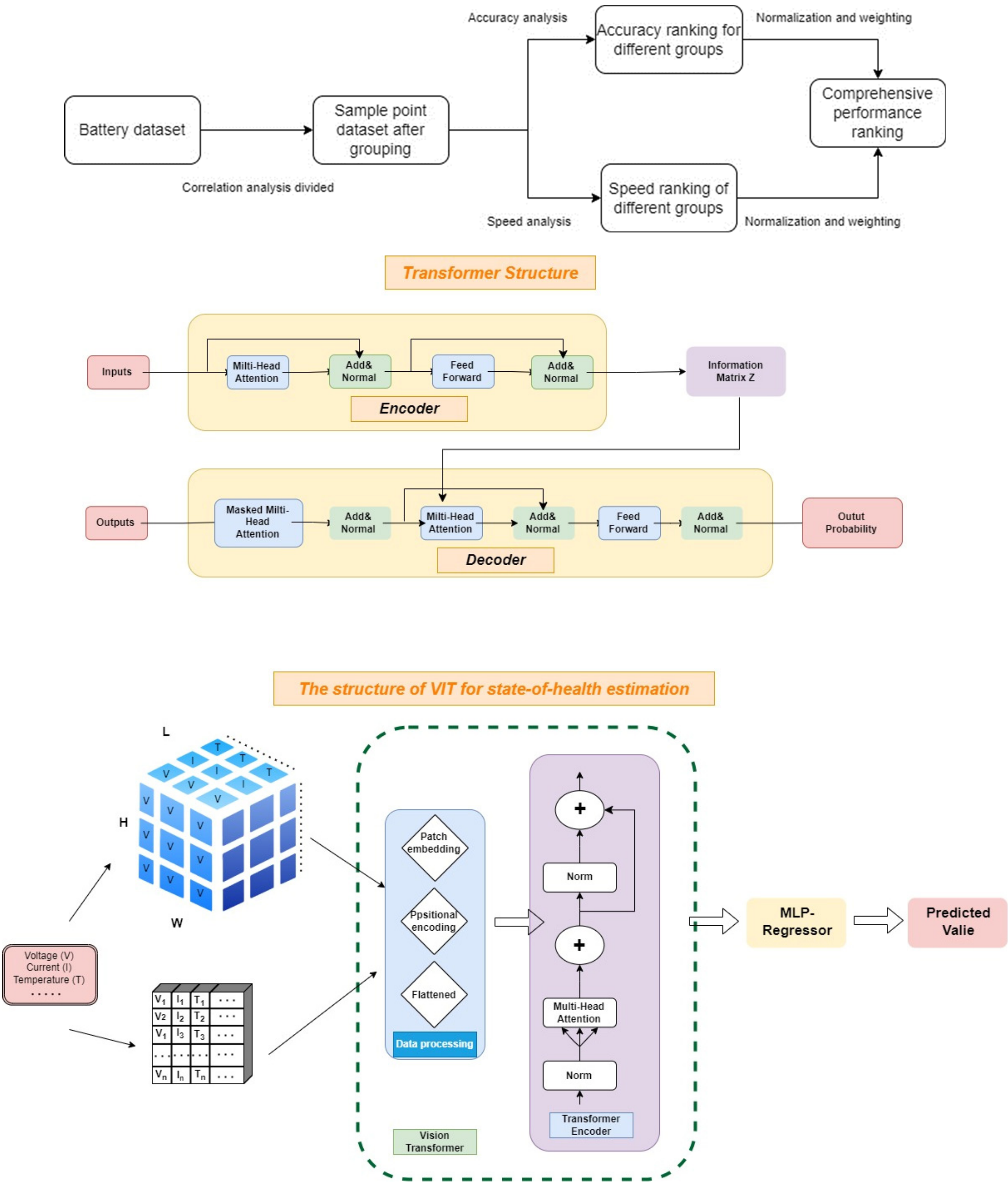

Figure 2. The algorithm flowchart [8].

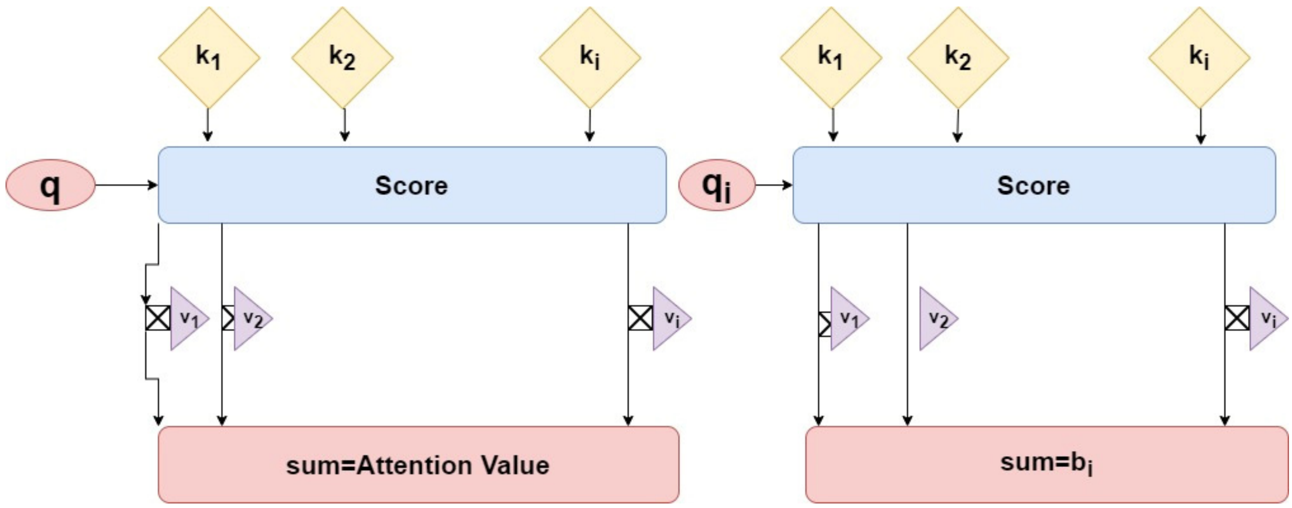

Figure 3. The calculation process of attention weight [9].

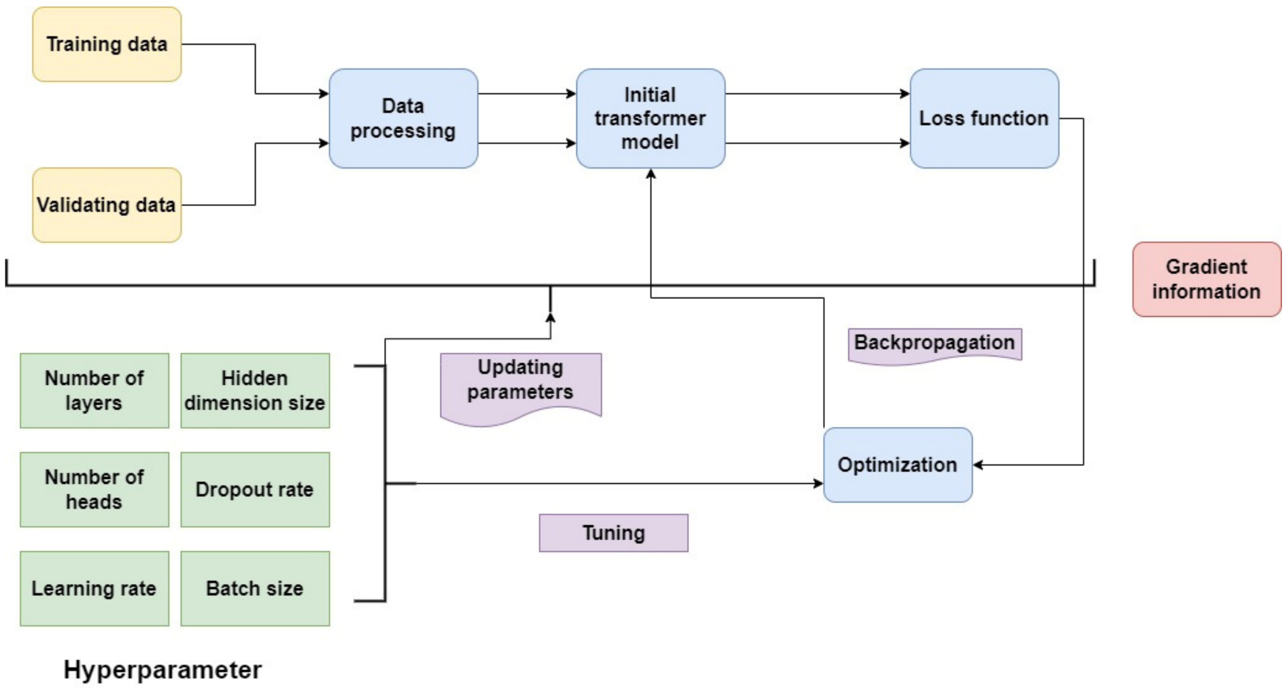

Figure 4. Hyperparameters of self-attention Transformer model [8].

2.2. Bidirectional Encoder Representations from Transformers

Liang et al. [9] introduced an advanced AI-based approach integrating self-attention and autoregression for predicting the SOH of LIBs. They demonstrated superior performance over current state-of-the-art (SOTA) methods on NASA and CALCE datasets, achieving significant reductions in root mean square error (RMSE) and mean absolute percentage error (MAPE). In contrast, Liu et al.'s [10] BERT-tery approach focuses on precise estimation of the state-of-charge (SOC) using time-resolved data from LIBs. It achieved highly accurate SOC estimations suitable for real-world applications, showcasing the potential for improved battery management. Additionally, Shi et al. [11] proposed a cloud-based AI-enhanced framework for co-estimating SOC and SOH, emphasizing the potential for enhanced battery management and performance forecasting under realistic operational conditions. Overall, the advantage of these AI-based approaches is their potential to significantly improve battery prediction accuracy and reliability, leading to more efficient battery health monitoring and management. However, they may require substantial computational resources and may not be universally applicable due to variations in battery system configurations and conditions, limiting their scalability. The effectiveness of these methods can also be influenced by the quality and quantity of the data used for training. Further research is needed to explore their generalizability across different LIB systems and conditions.

2.3. Attention Mechanisms

Several approaches have been proposed in recent research to improve the management and efficiency of LIBs. Yang et al. [12] presented a deep learning model with a dual-stage attention mechanism for accurately estimating the SOC in LIBs, particularly in electric vehicle (EV) applications. Their approach integrates domain knowledge about LIBs, including current, voltage, and temperature, to build an effective SOC estimation model. The model utilizes an encoder–decoder network based on gated recurrent units (GRUs) to capture temporal dependencies in sequential data. Wang et al. [13] focused on predicting the RUL of LIBs, which is crucial for effective management systems in various industrial applications. They proposed a model called the Bidirectional LSTM with Attention Mechanism (Bi-LSTM-AM), which incorporates continual parameter updates and employs a sliding window method for multi-step-ahead predictions of SOH based on normalized capacity. Hong et al. [14] addressed the prediction of temperature in LIBs in EVs, which is essential for ensuring safety and longevity. They proposed a clustering-based data partitioning method and a spiral self-attention neural network to capture complex dependencies and accurately predict temperature variations. Tian et al. [15] developed a two-stage optimization model to predict the SOH and RUL of LIBs using graph convolutional networks (GCNs) with attention mechanisms. Zhang et al. [16] proposed a hybrid neural network model, CNN-CBAM-LSTM, to predict the SOH of LIBs, which includes a CNN, convolutional block attention module (CBAM), and LSTM neural network. Xie et al. [17] combined an attention mechanism with a bidirectional LSTM network to predict the RUL of LIBs. Marri et al. [18] combined a bidirectional LSTM neural network with an attention mechanism to estimate the SOH in LIBs. Finally, Bao et al. [19] proposed a novel approach to predicting the health state of LIBs by integrating variational mode decomposition, an integrated filter, and a LSTM network with a self-attention mechanism. They decomposed LIBs capacity data into residual and intrinsic mode function components using variational mode decomposition, where the former encapsulates the global degradation trend while the latter captures local random fluctuations. The experimental results validated the effectiveness and stability of the proposed method, showcasing commendable prediction accuracy and promising avenues for accurately prognosticating the health status of LIBs.

2.4. Transformers for Time Series Analysis

Wan et al. [20] assessed the Convtrans model's efficiency in multi-step time series forecasting, particularly in predicting LIB temperature, demonstrating improved performance over traditional algorithms in terms of accuracy and trend prediction. Ge et al. [21] proposed a novel method that integrates wavelet threshold denoising and the transformer model to predict the RUL of LIBs, achieving accurate and generalized predictions even in the presence of data measurement noise. Nie et al. [22] developed an innovative SOH estimation methodology that combines advanced data preprocessing techniques with a fusion of CNN and the Transformer paradigm, achieving remarkable accuracy in SOH estimation.

Comparing the methods, all three address crucial aspects of LIB management and health estimation, including temperature prediction, RUL prediction, and SOH estimation. While Wan et al.'s [20] approach is specific to temperature forecasting, Hu et al.'s [6] focus on RUL, and Shi et al.'s [11] target SOH estimation, collectively they contribute to comprehensive LIB health monitoring and management. Moreover, they leverage advanced machine learning techniques such as Convtrans, wavelet threshold denoising, CNNs, and the Transformer model, indicating the growing trend of using sophisticated models to enhance LIB management.

However, each method has its limitations. For instance, Wan et al.'s [20] Convtrans model may have increased computational demands for multi-step forecasting over longer periods. Hu et al.'s [6] method may require careful selection of wavelet threshold denoising parameters to ensure accurate noise reduction. Shi et al.'s [11] approach could be affected by the quality and diversity of the input dataset, and further evaluation across a wider range of LIB conditions may be necessary to ensure its generalizability. These limitations highlight the need for continuous research and refinement in the fields of LIB management and health estimation.

3. Machine Learning Techniques

3.1. Unsupervised Learning

Zhang et al. [22] have made a significant contribution to the field of LIBs forecasting by developing an innovative forecasting system that combines EIS with Gaussian process machine learning. EIS, which is known for its real-time and non-invasive measurement technique, contains substantial information relevant to LIBs diagnosis, which the authors utilized to its fullest potential. The authors curated a vast dataset comprising over 20,000 EIS spectra from commercial Li-ion batteries, which spanned various states of health, states of charge, and temperatures, making it one of the largest datasets in the domain. The Gaussian process model they developed takes the entire EIS spectrum as input, eliminating the need for additional feature engineering. The model autonomously identifies relevant spectral features corresponding to degradation, showcasing its adaptability and robustness. An impressive aspect of Zhang et al.'s work is that their model can accurately predict the RUL of LIBs, even in cases where comprehensive information about the battery's past operating conditions is not available. This demonstrates the effectiveness of utilizing EIS signals in LIBs management systems and underscores the power of Gaussian process machine learning in providing precise forecasts of the SOH and RUL of Li-ion batteries. The findings of this study hold great promise for advancing LIBs technologies in various applications. By effectively leveraging EIS data and harnessing the capabilities of Gaussian process machine learning, this research enhances the performance, reliability, and overall effectiveness of LIB technologies, contributing significantly to the evolution of battery management and forecasting systems.

3.2. Meta-Learning

Jeong et al. [23] have introduced an innovative approach to estimating the SOC of Li-ion batteries by combining the concept of meta-learning with deep learning techniques. They developed a meta-learning SOC estimation algorithm that relies less on both pre-training and target battery data, leading to enhanced adaptability and a more rapid algorithm adaptation to the target battery. Their method achieved significantly lower SOC estimation errors compared to traditional transfer learning methods, showcasing strong performance under challenging conditions. Wang et al. [24] introduced the meta thermal runaway (TR) forecasting neural network (Meta-TRFNN), a data-driven approach aimed at accurately forecasting the TR state at the cell-level of LIBs. The Meta-TRFNN combines both high-dimensional thermal images and low-dimensional temperature and voltage data, capturing a comprehensive thermal profile and demonstrating strong performance in forecasting despite constrained historical data. Bai et al. [25] have taken a novel approach to enhance SOH estimation by applying meta-learning techniques. They developed a scalable and robust method for estimating the remaining capacity of LIBs solely based on data, significantly improving the accuracy and efficiency of SOH estimation for LIBs. To tackle the inherent data deficiency issue, the authors employed a meta-learning framework, as illustrated in Figure 5.

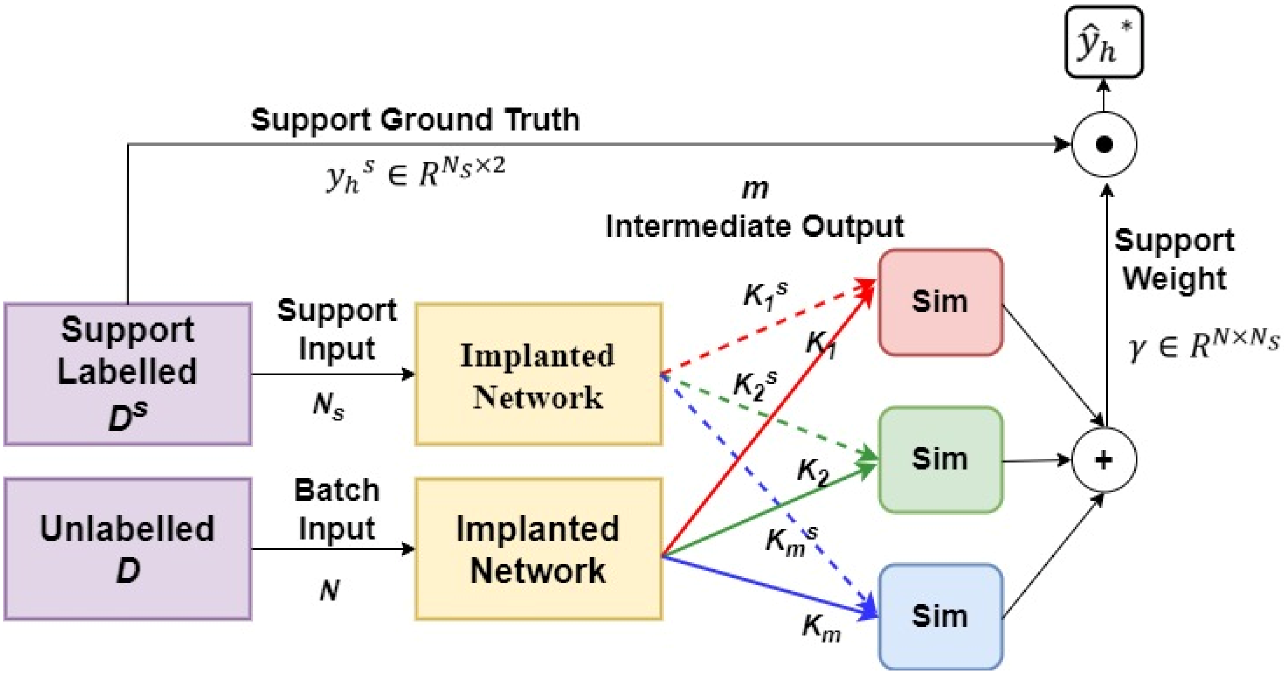

Figure 5. Meta-learning framework: a labeled support dataset D^s and an unlabeled dataset D are simultaneously sent to the implanted network. Subsequently, m intermediate outputs $\{K\eta^S\}_{\eta=1,...,m}$ are separately computed. At that time, the sum of the cosine similarities between $\{K\eta\}_{\eta=1,...,m}$ and $\{K\eta^S\}_{\eta=1,...,m}$ is considered the support weight $\gamma \in R^{N \times N_S}$. Finally, the supporting ground truth $\hat{y}_h^*$ is weighted by γ to generate the final output $\hat{y}_h^*$ [23].

In comparison, the meta-learning-based SOC estimation algorithm introduced by Jeong et al. [23] stands out for its ability to reduce reliance on specific target battery data and adapt quickly to target batteries. The Meta-TRFNN developed by Wang et al. [24] is notable for its robust performance in forecasting the TR state in LIBs despite data limitations, and Bai et al. [25] approach is significant for enabling continuous monitoring of SOH in EV batteries without extensive cycling and capacity measurements. Despite their strengths, all methods may have computational costs and limited generalizability, requiring further research to validate their scalability and effectiveness across different LIB systems and conditions. Further, the Meta-TRFNN developed by Wang et al. [24] and the meta-learning-based SOC estimation algorithm introduced by Jeong et al. [23] demonstrate potential for practical applications and promise in enhancing battery health monitoring and management.

3.3. Adversarial Training

Ye et al. [26] developed a novel deep domain adversarial network (DDAN) to estimate the SOH of LIBs. This approach utilizes adversarial training and unsupervised feature alignment metrics, improving the accuracy and practicality of SOH estimation for real-world applications. Additionally, Ren et al. [27] proposed a strategy that combines adversarial learning and feature selection to enhance deep learning-based lifespan estimation for LIBs. Their study effectively improved the accuracy of lifetime estimation through adversarial feature selection strategies. Zou et al. [28] introduced a regression GAN approach for SOH estimation. Their research focuses on creating a generalized model tailored to batteries with specific specifications, considering the challenges associated with measuring real SOH during battery operation. The method uses a generator that automatically creates auxiliary training samples with distributions similar to actual samples and a discriminator that learns the distribution of authentic samples. Moreover, Ardeshiri et al. [29] focused on developing a novel prognostic architecture for predicting the degradation of LIBs and estimating their RU, crucial for battery management systems. The proposed method utilizes a least-squares generative adversarial network, with a gated recurrent unit as the generator and a multi-layer perceptron as the discriminator. This approach aims to learn the probability distribution of future values through adversarial training, giving more weight to large errors and mitigating the vanishing gradient problem during training. To enhance prediction accuracy, time-domain features are extracted using statistical formulas, and the most significant features are selected using the random forest algorithm. These features are then fed into the network as a multivariate input set. The performance of the method is evaluated using a dataset from NASA's Prognostics Center of Excellence, as well as experimental data from lithium-ion cells tested at different current rates. The results indicate that the proposed model achieves a low prediction error of 2.63% and a maximum absolute error of 0.02, demonstrating its effectiveness in predicting the RUL of LIBs. Lastly, Nandhini et al. [30] introduced an unsupervised methodology using GANs to extract reliable latent variables from EIS data, showcasing accurate capacity estimation results when compared to traditional methods. Furthermore, Zhao et al. [31] combined GAN-conditional latent space (GAN-CLS) with bidirectional long short-term memory (BLSTM) to predict the state of rechargeable LIBs, achieving reduced time requirements and enhanced accuracy.

Overall, the different methodologies presented in the studies address various challenges related to LIB health diagnostics, ranging from SOH estimation, lifespan estimation, and RUL prediction to capacity estimation and state prediction. They leverage advanced techniques such as adversarial learning, feature selection, and GANs to improve the accuracy and efficiency of battery diagnostics, demonstrating promising results across different working conditions and datasets. However, each method also has its limitations. For example, the regression GAN approach may struggle with complex data scenarios, while unsupervised methodologies may require substantial computational resources for training. Figure 6 illustrates GAN architecture.

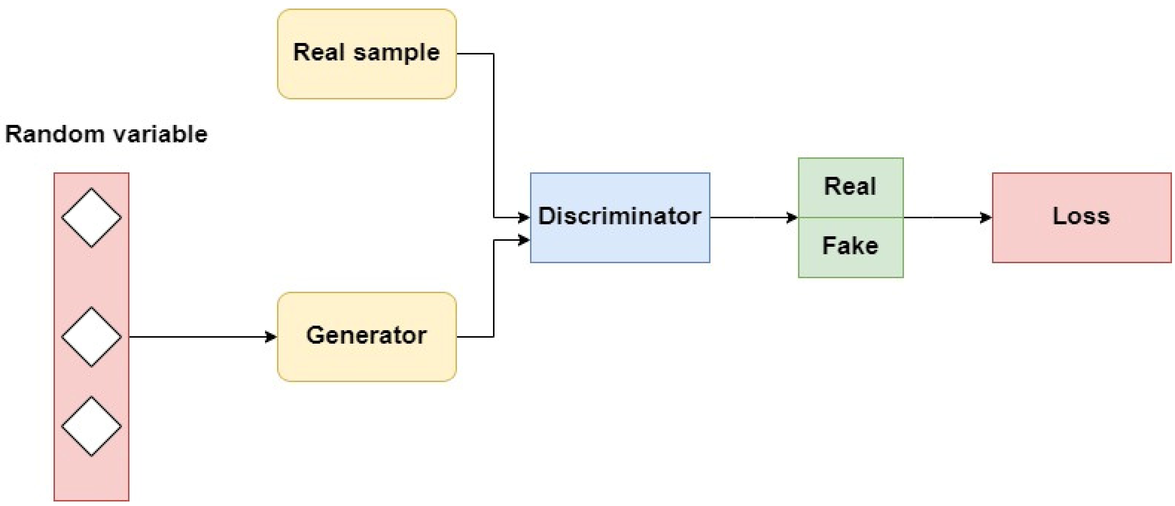

Figure 6. GAN architecture [31].

3.4. Neural Architecture Search

Hannan et al. [32] address the critical task of accurately determining the SOC in LIBs commonly found in EVs. The authors enhance the back-propagation neural network (BPNN) model by integrating the backtracking search algorithm (BSA) optimization technique. This optimization method fine-tunes key parameters such as hidden layer neurons and learning rate within the BPNN, significantly improving the model's accuracy and robustness. The approach is rigorously evaluated using various driving profiles and temperature conditions, including the dynamic stress test and the Federal urban driving schedule. The enhanced BPNN model, compared to other neural network models like the radial basis function neural network and generalized regression neural network, outperforms in SOC estimation accuracy across different driving profiles and temperatures. This study highlights the effectiveness of the BPNN model augmented with BSA optimization in enhancing SOC estimation accuracy for LIBs used in EVs.

3.5. Self-Supervised Learning

The studies by Hannan et al. [32], Che et al. [33], and Hannan et al. [34] focus on improving the SOC and SOH estimation for LIBs, particularly in EV applications. Hannan et al. [32] introduced a novel deep learning-based transformer model trained using self-supervised learning (SSL) techniques for SOC estimation. The model demonstrates high accuracy in SOC prediction, even in variable ambient temperature conditions, and exhibits robustness to temperature variations. Additionally, the learning weights from the SSL training process exhibit transferability, enabling the model to perform well on new LIBs with different chemistries. Che et al. [33] proposed a self-supervised learning framework for SOH estimation. Their approach uses filter-based data preprocessing and an auto-encoder–decoder network to learn aging characteristics from unlabeled data. The framework achieves accurate SOH estimations across various LIB chemistries, formats, and operating conditions with only three labeled data points, showcasing its efficiency and accuracy in estimating SOH. Hannan et al. [32] presented another deep learning-based transformer model for SOC estimation, which demonstrated exceptional performance with the lowest RMSE at 1.2% and an MAE of just 0.7% on the test dataset. Like Hannan et al. [32], this model was also trained using self-supervised learning principles and maintained high accuracy even in varying ambient temperatures. Overall, the three studies highlight the effectiveness of deep learning approaches, especially when combined with self-supervised learning techniques, in improving the accuracy, efficiency, and adaptability of SOC and SOH estimation for LIBs in EV applications. Figure 7 illustrates the Architecture of a Bi-LSTM with attention mechanism.

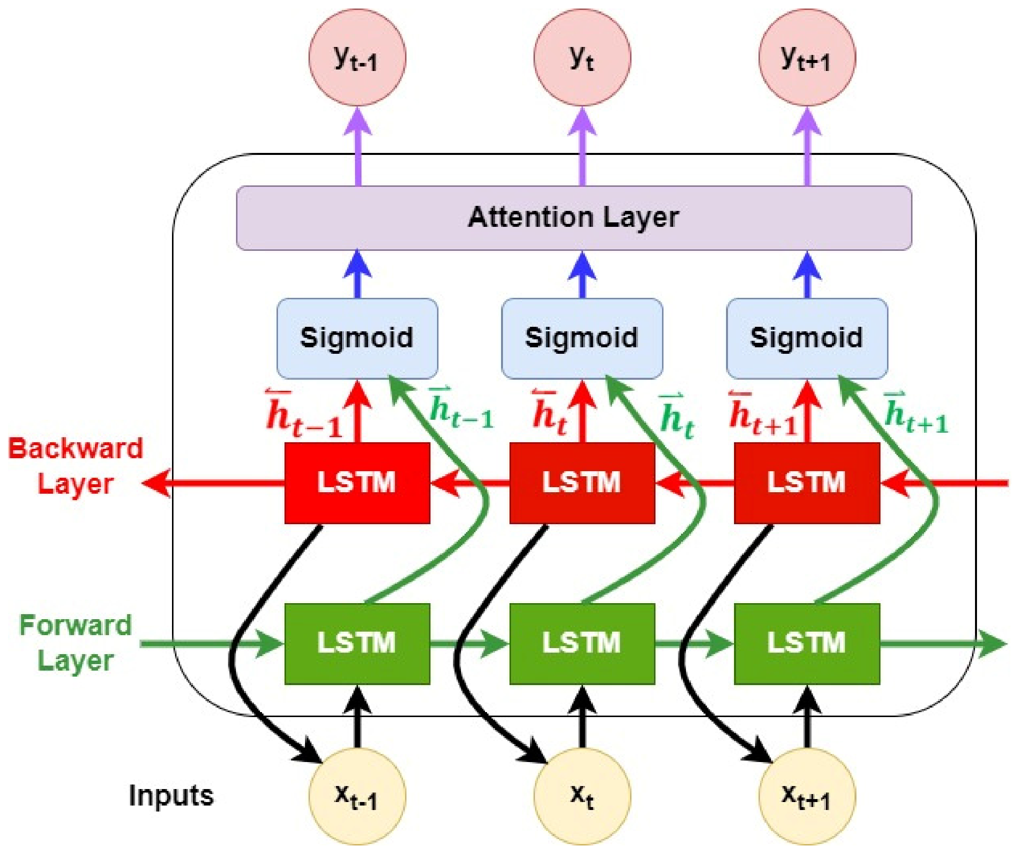

Figure 7. The Architecture of a Bi-LSTM with attention mechanism [32].

3.6. Capsule Networks

Jonathan et al. [35] enhanced the efficiency of predicting the RUL of LIBs, crucial for their second-life classification. The article introduces a capsule network architecture, leveraging transfer learning, for swift battery RUL prediction. This method accurately forecasts a cell's RUL after just one charging and discharging cycle, making it exceptionally rapid. By employing images that encapsulate complete cycles and even numerical data, the model reduces preprocessing efforts and human-induced biases. This innovation will benefit second-life battery classification, aid in developing health-conscious charging protocols, and enhance battery management systems.

3.7. Differentiable Neural Computers

The works by Sun et al. [36] and Navega et al. [37] both contribute innovative methodologies for enhancing the monitoring and management of LIBs, specifically focusing on thermal fault detection and SOC estimation, respectively.

Sun et al. [36] proposed a neural network-based approach for thermal fault detection in LIBs, utilizing a long short-term memory (LSTM) neural network, which is a type of recurrent neural network (RNN) known for capturing long-term dependencies in time-series data. The incorporation of a modified walk-forward technique and a residual monitor serves to enhance the accuracy and real-time detection capabilities of the approach. The design's simplicity and adaptability to various datasets make it practical for handling real-world scenarios effectively.

On the other hand, Navega et al. [37] introduced a dual neural network fusion model for SOC estimation, consisting of a linear neural network LIBs model and a backpropagation (BP) neural network. This model is trained using dynamic stress test (DST) data to establish the relationship between open circuit voltage (OCV) and SOC, enabling accurate SOC estimations under various operational conditions. The integration of electrochemical behavior representations and OCV-SOC relationship estimate ion enhances the efficiency and effectiveness of LIBs management and control systems.

Overall, both methodologies contribute to the advancement of LIBs monitoring and management, with Sun et al. [36] focusing on real-time thermal fault detection Navega et al. [37] concentrating on accurate SOC estimation. Both approaches offer promising solutions to challenges faced in LIBs applications and hold potential for practical implementation in real-world scenarios.

3.8. Continual Learning

Sun et al. [36] investigated various regularization strategies within the context of continual learning, specifically focusing on LIBs degradation datasets. Their study aimed to evaluate and compare different approaches to continual learning within regularization strategies using authentic LIBs degradation data. They implemented and thoroughly assessed multiple regularization strategies, comparing them based on task characteristics and the sequence of task execution. The study found that the approach known as online elastic weight consolidation demonstrated the most promising outcomes among the evaluated strategies. Performance was observed to be influenced by the specific characteristics of tasks and the sequence in which tasks were executed. Figure 8 in the study illustrates the architecture of the base algorithms' deep neural networks for non-regularized regression and regularized classification tasks. The findings provide insights into the effectiveness of different regularization strategies in the context of continual learning for LIBs degradation, highlighting online elastic weight consolidation as a particularly promising approach.

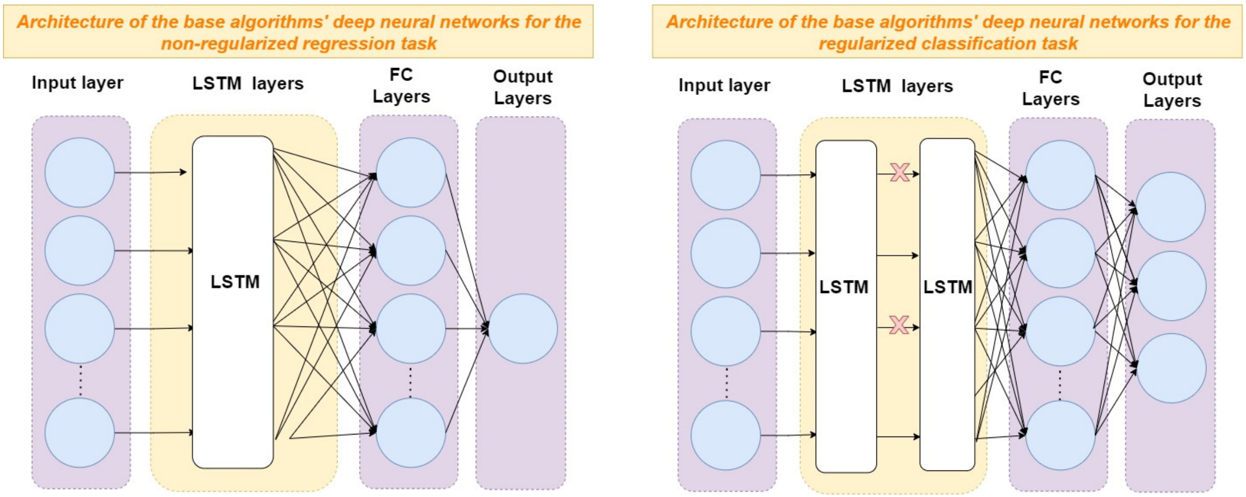

Figure 8. The architecture of the base algorithms' deep neural networks for the non-regularized regression task and the regularized classification task [36].

3.9. Reinforcement Learning

Cao et al. [38] have developed a groundbreaking methodology for accurately estimating the degradation cost of LIBs to optimize their participation in the energy arbitrage market. This model-free deep reinforcement learning (DRL) approach frames the control challenge as a Markov decision process (MDP), using noisy networks to acquire an optimized control policy for charging and discharging strategies, considering LIBs' degradation patterns. The integration of CNN and LSTM architectures for forecasting electricity prices contributes to improved decision making in energy arbitrage. By comprehending the inherent uncertainty in LIBs' degradation patterns, the DRL approach ensures energy arbitrage actions do not harm their health. Validation using historical U.K. wholesale electricity market prices demonstrates the framework's superior performance and efficacy compared to traditional methods. This methodology has the potential to enhance LIBs' participation in the energy domain, improving economics and viability.

3.10. Multi-Task Learning

The methodologies proposed by Li et al. [39], Bao et al. [40], and Che et al. [41] all aim to enhance LIB management and health estimation through advanced data-driven approaches. Li et al. [39] developed a multi-task learning framework to predict concurrent degradation of capacity and power in early-life stages of LIBs, demonstrating robust performance and superiority over single-task learning methods. Bao et al. [40] introduced a multi-task learning network (MTL) for estimating LIBs' SOC and state-of-energy (SOE), achieving impressive accuracy and efficiency compared to other multi-task learning models. Che et al. [41] proposed a method for online end-to-end state monitoring using transferred multi-task learning with a CNN, showcasing superior accuracy and computational efficiency across diverse application scenarios. These approaches collectively represent significant advancements in data-driven prognostics and state estimation for LIBs, offering improved accuracy and efficiency in LIB management. However, potential limitations of these methods may include the need for extensive computational resources, specific data requirements, and challenges in real-world implementation and validation. Further research and development are needed to address these limitations and fully exploit the potential of data-driven approaches in LIB management. Figure 9 shows the proposed multi-task learning network.

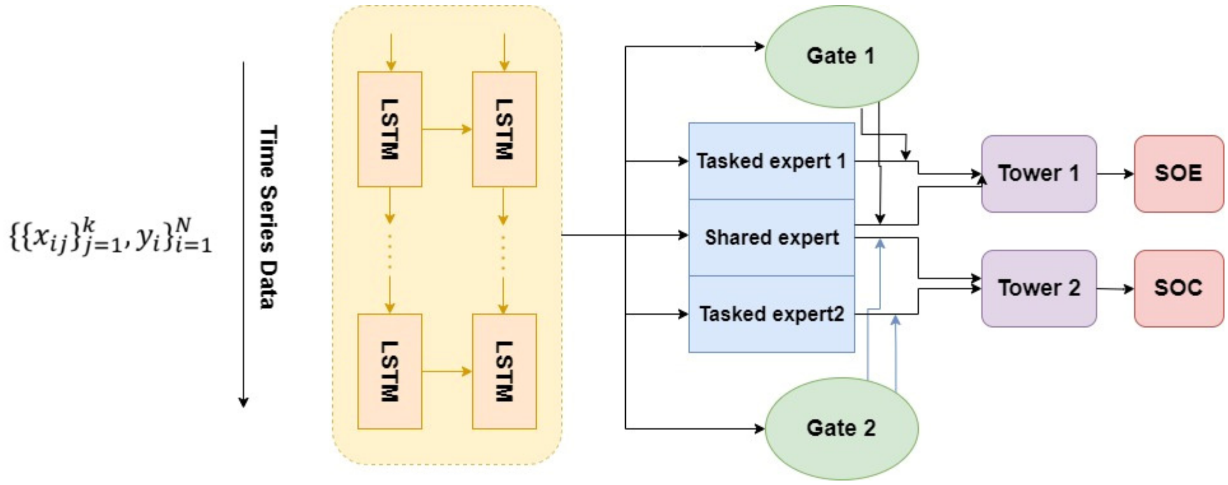

Figure 9. The proposed multi-task learning network [40].

3.11. Memory-Augmented Neural Networks

Fei et al. [42] have developed an innovative approach to predict the RUL of LIBs using a modest dataset sourced from only 10 incomplete cycles. Their proposed "attention-assisted temporal convolutional memory-augmented network" (ATCMN) framework, a sophisticated deep learning architecture, addresses the challenge of RUL prediction with limited data. A key aspect of their approach is the introduction of a three-dimensional tensor input structure that incorporates temporal, capacity, and temperature dimensions from the limited data. An attention module assigns weights to LIBs parameters, time steps, and aging cycles for efficient information assimilation, while a temporal convolution module learns latent spatial-temporal features. A memory-augmented module enhances latent feature representation through a reconstruction process rooted in historical data, and a prediction module crafts nonlinear mappings based on acquired latent features for accurate LIBs RUL predictions. Computational evaluations show that the ATCMN framework offers superior prediction precision and speed compared to state-of-the-art methods. It also exhibits enhanced adaptability across different LIBs chemistries and operational conditions. Fei et al.'s ATCMN framework marks a paradigm shift in LIBs RUL prediction by efficiently navigating the constraints of limited data from incomplete cycles, setting a new benchmark for prediction accuracy and efficiency compared to established methodologies. This pioneering solution offers accuracy and efficiency even with a limited dataset, showcasing adaptability across diverse operational conditions.

3.12. Generative Models for Data Augmentation

The data augmentation methodologies proposed by Cui et al. [43] and Zhao et al. [44] both aim to improve LIB health prediction by enhancing the accuracy of SOH and other critical parameters such as SOC. by Cui et al. [43] leverage the quantum assimilation algorithm to construct a potential energy landscape, allowing for a unique exploration of the feature space and more accurate SOH predictions, especially for LIBs with distinct degradation trajectories. On the other hand, Zhao et al. [44] introduce a GAN-based approach to generate synthetic time-series data, aiming to expand sparse datasets and improve the learning capabilities of neural networks in estimating SOC and SOH. Both methodologies offer innovative solutions to enhance the accuracy and reliability of LIB health prediction, with potential implications for battery management systems. However, potential limitations of these methods may include the need for extensive computational resources or specific data requirements, as well as challenges in real-world implementation and validation. Further research and development are needed to address these limitations and fully exploit the potential of data augmentation strategies in LIB management.

Both approaches offer innovative solutions to improve the accuracy and reliability of LIB management and health prediction. Cui et al. [43] quantum assimilation-based method focuses on refining SOH prediction in LIBs with complex degradation patterns, providing insights into complex battery behaviors, and outperforming traditional methodologies. On the other hand, Zhao et al. [44] GAN-based approach addresses the challenge of sparse data in battery parameter estimation by generating synthetic data, thus enhancing the robustness and accuracy of battery state estimation models. While both methods have the potential to revolutionize the field of battery health prediction, they may also have their limitations, such as the need for extensive computational resources or specific data requirements. Further research and development are needed to address these limitations and fully exploit the potential of data augmentation strategies in LIB management.

3.13. Logistic Regression

References [45,46] are provided as sources for information on logistic regression as a statistical classification technique. Reference [47] is mentioned specifically for insights into the application of logistic regression in fault detection and diagnosis in the LIB system.

Logistic regression (LR) is a statistical technique commonly used in binary classification tasks but can be adapted for multi-class classification, such as categorizing the condition of LIBs. LR is straightforward and interpretable, but it may not capture complex nonlinear relationships effectively. While LR is useful for categorical classification, it is recommended to explore more advanced methods like neural networks or decision trees, depending on the complexity of the monitoring challenge. The paper highlights LR's simplicity and effectiveness in two-class classification tasks but suggests that it has been underutilized in LIB fault detection and diagnosis. Researchers are encouraged to consider alternative machine learning algorithms beyond LR to address more complex monitoring scenarios.

4. Specific Applications

4.1. A Machine Learning-Based Digital Twin

Sidahmed et al. [48] have presented a sophisticated battery digital twin framework that relies on data-driven models trained using historical data to accurately represent the real-time dynamics of a battery. This framework incorporates a SOH model that estimates the battery's capacity degradation and a SOC model that accounts for aging effects, offering a comprehensive representation of battery behavior over time. The authors have demonstrated the effectiveness of this digital twin by applying it to a publicly available dataset, showcasing its high accuracy and compatibility with onboard execution. Sidahmed et al.'s battery digital twin framework represents a significant advancement in real-time battery modeling with potential applications in EVs and energy storage systems, offering a robust solution for dynamic and accurate battery behavior representation.

4.2. Digital Twins for Electric Vehicle SoX Battery Modeling

Zhao et al. [49] conducted a comprehensive review of the existing state and challenges related to battery systems and introduced a digital twin framework specifically designed for accurately capturing the SOC during runtime operations. The digital twin framework is built upon data-driven models trained using historical battery performance data, with an emphasis on accurately handling complex nonlinear behaviors of batteries. The framework includes periodic retraining of models to account for battery aging effects and was applied to two publicly available datasets, with practical examples illustrating its utility and effectiveness. The study encourages the adoption of the digital twin framework for batteries, highlighting its capabilities in accurately representing battery behavior and enhancing adaptability to real-world performance.

4.3. A Brain-Inspired Spiking Network Framework Based on Multi-Time-Step Self-Attention

While artificial neural networks (ANNs) have been effective in monitoring battery health, they suffer from drawbacks such as high energy consumption and limited generalization. In contrast, recent advancements in brain-inspired spiking neural networks (SNNs) offer promising features like efficient spatiotemporal feature learning similar to biological brains, with low power consumption. Wang et al. [50] introduced a novel approach called Multi-Time-Step Self-Attention Spiking Neural Network (MSSA-SNN) for battery monitoring. Specifically, the SNN-based self-attention module captures comprehensive spiking features globally and optimizes synaptic weights from a holistic perspective. Experiments conducted on two datasets of coin Li-ion batteries demonstrate that MSSA-SNN accurately detects trends in battery degradation with remarkably low energy consumption. This capability makes MSSA-SNN particularly suitable for energy-constrained consumer electronics applications.

4.4. Applications of Random Forest (RF) Classifier

Random forest classifiers were used for various applications, including vehicle trajectory prediction, image classification, facial expression recognition, fault diagnosis, and sleep stage classification [51–56]. The random forest (RF) classifier is a supervised machine learning method that has shown effective performance in a variety of classification tasks, including those listed in Table 1.

Table 1. Different applications of Random Forest (RF) Classifiers.

<table>
<tr><th>Applications</th><th>Characteristics</th><th>Ref.</th></tr>
<tr><td>Sleep stage classifications from electroencephalography (EEG) data.</td><td rowspan="6">• Enhanced robustness through collaboration among trees in random forest (RF).
• Random Forest is characterized as a linear classifier.
• Demonstrates reduced computational complexity compared to certain other widely used classifiers.
• Well-suited for lightweight algorithms, facilitating real-time operations.
• Convenient feature scaling is supported.
• Enables parallel operation, complementing the primary usage of the system.</td><td>Bakmeedeniya, et al. [55]</td></tr>
<tr><td>Bearing fault identification from vibration data.</td><td>Hu et al. [57]</td></tr>
<tr><td>Facial expression detection from video data.</td><td>Maschler et al. [58]</td></tr>
<tr><td>Crop type classification from hyperspectral images.</td><td>Wang et al. [59]</td></tr>
<tr><td>Lung vessel segmentation from computed tomography (CT) images.</td><td>Zhao et al. [60]</td></tr>
<tr><td>Mention of many more applications.</td><td>Zhang et al. [61]</td></tr>
</table>

5. Graph-Based Models

5.1. Graph Neural Networks

Both Wang et al. [62] and Wei et al. [63] propose innovative approaches that utilize advanced machine learning techniques to address key challenges in LIB management, such as accurate capacity estimation, SOH prediction, and RUL prediction. Wang et al. [62] leverage a graph neural network (GNN) to estimate LIB capacity by integrating diverse sensor measurements into a graph-like structure. They use neural architecture search to select data aggregation and feature fusion operations, improving model adaptability. Wei et al. [63] employ graph convolutional networks (GCNs) with attention mechanisms to enhance the prediction accuracy of SOH and RUL. They construct an undirected graph using optimal graph entropy to capture intricate relationships among various features in the LIB system. Both approaches demonstrate superior performance compared to existing data-driven methodologies, showcasing impressive predictive accuracy and robustness.

These approaches offer several advantages, such as enhanced prediction accuracy, adaptability, and robustness in noisy environments. By leveraging advanced machine learning techniques, they overcome the limitations of conventional methods and improve LIB health management applications. However, these methods may also have some limitations. For example, they may require large amounts of data for effective training, and the performance of these models can be influenced by the quality and quantity of the input data. Additionally, the computational complexity of these techniques may be high, requiring significant computational resources for training and inference. Nevertheless, the proposed approaches represent promising tools for LIB health management and safety, offering improved accuracy and reliability compared to existing methods.

Wang et al. [62] have made a transformative breakthrough in the realm of LIB capacity estimation with their pioneering approach. Traditional methods for LIB capacity estimation have been hindered by hand-crafted feature engineering or complex data-driven approaches requiring intricate network designs and laborious trial-and-error iterations. However, Wang et al.'s ingenious solution ingeniously organizes LIBs measurements from multiple sensors into a complex graph structure. This architectural foundation, combined with the powerful capabilities of graph neural networks (GNNs), facilitates a holistic and dynamic data fusion process, enhancing the network's capacity and contributing to improved estimation accuracy. Moreover, they incorporate neural architecture search, which automates optimization, streamlines manual network design, and fortifies the network's adaptability and resilience. The extensive validation using two publicly available datasets confirms the efficacy of their approach, demonstrating not just promising but revelatory results. Their in-depth analysis highlights the intrinsic potential of GNNs and the critical role played by architecture searching in ensuring robustness and dependability, particularly in noisy environments. This amalgamation of GNNs and neural architecture search is a pivotal turning point, ushering in heightened efficiency and pinpoint accuracy in LIBs health management through remarkably improved capacity estimation. Wang et al.'s innovative approach represents a significant advancement in accurately estimating the capacity of LIBs, with potential implications for enhancing LIBs health management overall.

5.2. A Physics-Informed Machine Learning

The model structure of the pre-trained CNN model, is illustrated in Figure 10. The methodologies from Cho et al. [64], Li et al. [65], Wang et al. [66], El-Dalahmeh et al. [67], and Tan et al. [61] all focus on improving the performance, efficiency, and accuracy of battery technologies, specifically in predicting temperature for LIB cells, streamlining CNN models for better estimation performance with limited datasets, estimating the capacity of lithium-ion (Li-ion) cells, diagnosing degradation of LIBs through time-frequency image (TFI) analysis and transfer deep learning algorithms, and predicting the SOH in LIBs, respectively. The structure of the DCNN-ETL model is demonstrated in Figure 11. Cho et al. [64] utilize physics-informed neural networks (PINNs) to accurately predict LIBs' temperature without requiring extensive training data or explicit physics equations, while Li et al. [65] introduce a framework that strategically combines transfer learning and network pruning to create streamlined CNN models with enhanced estimation performance. The architecture of one among n DCNN-TL models constituting the proposed DCNN-ETL mode is illustrated in Figure 12. Wang et al. [66] employ a cutting-edge methodology that leverages transfer learning and ensemble learning to estimate the capacity of Li-ion cells, and El-Dalahmeh et al. [67] propose a pioneering methodology that combines time-frequency image (TFI) analysis with a transfer deep learning algorithm to extract diagnostic attributes related to LIBs' degradation. Lastly, Ye et al. [68] focus on predicting the SOH in LIBs by addressing the issue of limited training data through transfer learning. Each methodology has its advantages and disadvantages. Flowchart of the proposed model for TFI capacity estimation is demonstrated in Figure 13. Cho et al. [64] offer a method that does not require extensive training data or explicit physics equations but may not be as accurate as methods that utilize more data. Li et al. [65] and Wang et al. [66] utilize transfer learning and ensemble learning to improve estimation performance but may require a large source dataset for pre-training. El-Dalahmeh et al. [67] use TFI analysis and transfer deep learning to accurately predict the capacity of LIBs, but this may require more computational resources. Ye et al. [68] overcome the limitations of training data by integrating knowledge from one task to improve predictions in a related task, but this approach may have limitations in certain scenarios where there is not a strong foundation for transfer learning. A comparison between different studies is described in Table 2. The architecture of LSTM-FC is shown in Figure 14.

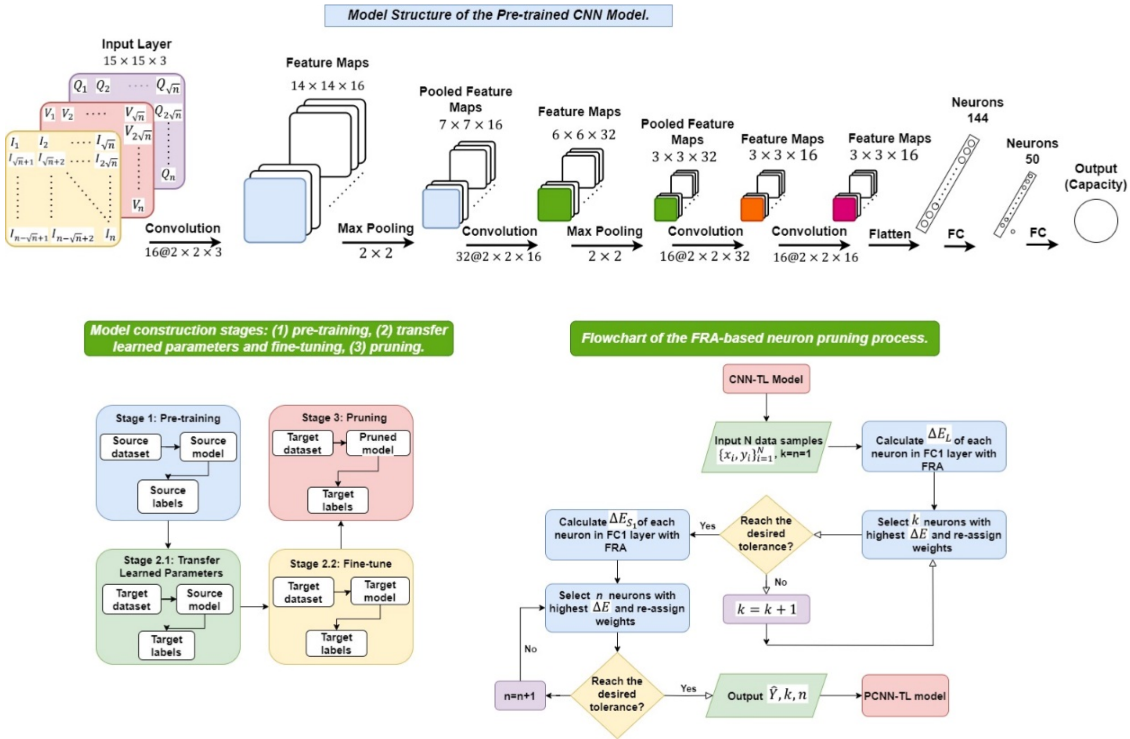

Figure 10. Model structure of the pre-trained CNN model, model construction stages: (1) pre-training, (2) transfer learned parameters and fine-tuning, (3) pruning; and flowchart of the FRA-based neuron pruning process. In this model, a nonlinear discrete-time dynamic system is represented by a linear-in-the-parameters model, which is identified by N data samples $\{x_i, y_i\}_{i=1}^{N}$, ΔE_L: the net contribution of the L th model term, L: Number of neurons inputted to the first fully connected layer, Y: Model output, n: Data segmentation length, S_1: Number of neurons inputted to the second fully connected layer [65].

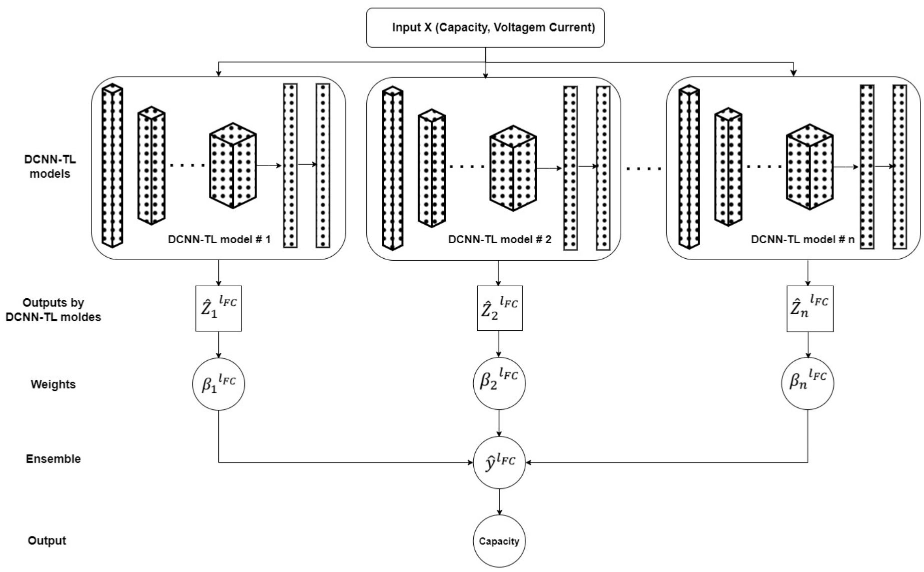

Figure 11. The structure of the DCNN-ETL model [59]. The ith row and jth column of kth output of the convolutional layer l_{conv} can be expressed as $Z_{i,j,k}^{l_{conv}} = C(X,K)_{i,j,k} = \Sigma_{r=1}^{k_h}\Sigma_{s=1}^{k_w}\Sigma_{\acute{t}=1}^{k_c} x_{\acute{i},\,\acute{j},\,\acute{t}}.k_{r,s,\,\acute{t},k} + b_k$; $\acute{i} = (i-1).s_h + r$; $\acute{j} = (j-1).s_w + s$; where $k_{r,s,\,\acute{t},k}$ and b_k represent the weights and bias of the k^{th} kernel in the convolutional layer, respectively. The outputs of n individual DCNN-TL models, $\hat{Z}_n^{l_{FC}}$, were obtained by a fully connected ensemble layer. This layer was used to assign the model weights, ${\beta_n}^{l_{FC}}$, to $\hat{Z}_n^{l_{FC}}$ and compute an estimated target for the input sample, $\hat{y}^{l_{FC}} = {\beta_n}^{l_{FC}}\hat{Z}_n^{l_{FC}}$ [66].

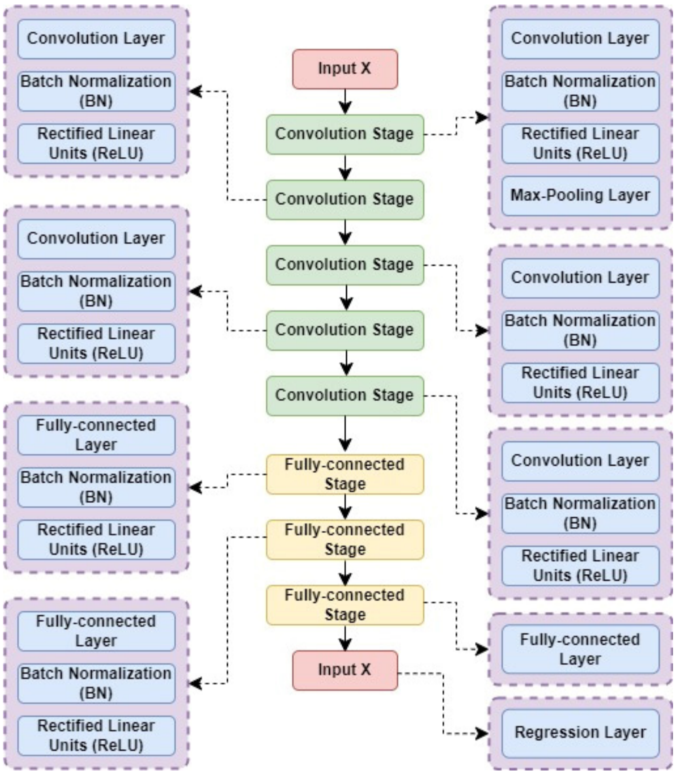

Figure 12. Architecture of one among n DCNN-TL models constituting the proposed DCNN-ETL mode [66].

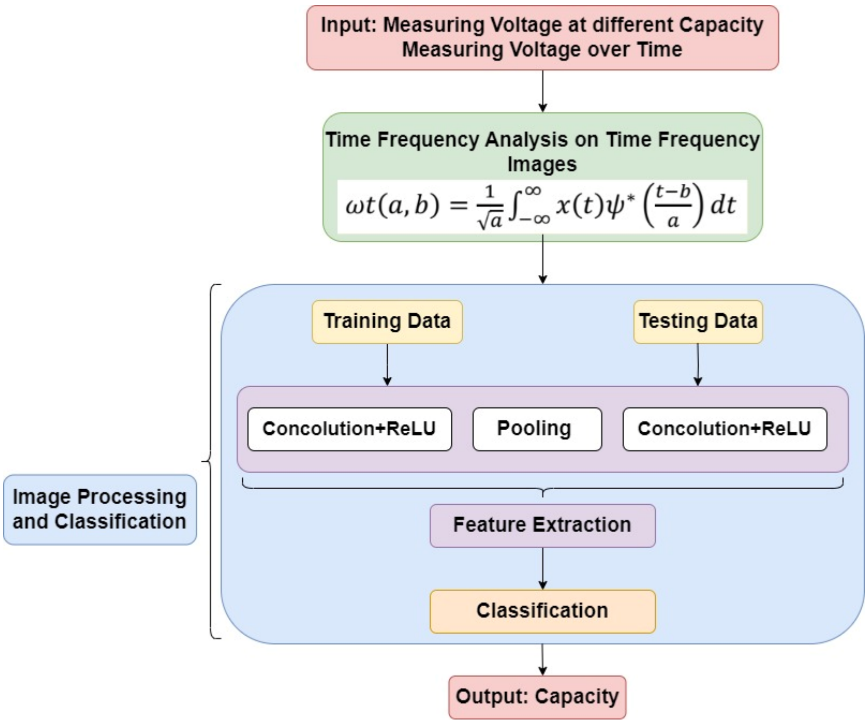

Figure 13. Flowchart of the proposed model for TFI capacity estimation. For the time series signal $x(t)$, the wavelet coefficients are obtained by the convolution integral of the mother wavelet ψ(t) and the given signal $x(t)$, as proposed in $\omega t(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt$ [67].

Table 2. A comparison between different studies.

Investigation/Methods	Advantages	Disadvantages	Contribution	Ref.
Precise estimation of the SOC using time-resolved data from LIBs	Achieves highly accurate SOC estimations suitable for real-world applications	May have computational demands	Offers potential for improved battery management especially in real-world scenarios but may require careful consideration of computational resources	[3,4]
Transformer-based Neural Network with De-noising Auto-Encoders	Offers high accuracy in RUL prediction	Requires extensive data and computational resources	Proposed a Transformer-based neural network combined with De-noising Auto-Encoders (DAE) for improved RUL prediction of LIBs	[5,6]
Integrated wavelet denoising and transformers for RUL prediction	Accurate and generalized predictions even with data measurement noise	Wavelet threshold denoising parameters must be carefully selected for accurate noise reduction	Accurate RUL prediction with wavelet denoising and transformers	[6]
CNN-Transformer Framework	Offers high accuracy in SOH prediction	Can be computationally intensive	Introduced a comprehensive approach integrating data pre-processing and a CNN-Transformer framework for high-accuracy SOH estimation	[7,11]
Combined data preprocessing CNNs and Transformers for SOH estimation	Remarkable accuracy in SOH estimation innovative approach	May be affected by input dataset quality and diversity further evaluation across a wider range of conditions may be necessary for generalizability	Precise SOH estimation with CNN-Transformer fusion	[7,11]
Bi-LSTM-AM for RUL Prediction	Effective for multi-step ahead predictions of SOH; continual parameter updates	Requires ongoing parameter tuning; may have computational demands	A model combining bidirectional LSTM with attention mechanism for RUL prediction	[7]
Proposes a cloud-based AI-enhanced framework for co-estimating SOC and SOH	Shows potential for enhanced battery management and performance forecasting	May have computational demands and may not be universally applicable	Offers potential for improving battery management but may require careful consideration of computational resources and applicability	[11]
Dual-Stage Attention Mechanism for SOC Estimation	Effective SOC estimation particularly in EV applications	Complexity may affect computational efficiency	A deep learning model integrating domain knowledge and attention mechanisms for SOC estimation in LIBs	[12]
Utilizes self-attention and autoregression for SOH prediction of LIBs	Demonstrates superior performance over existing methods such as significant reduction in RMSE and MAPE	Requires substantial computational resources and may not be universally applicable due to variations in battery system configurations and conditions	Offers potential to significantly improve battery prediction accuracy and reliability but requires careful consideration of computational resources and applicability	[13]
Neural Network-Based Thermal Fault Detection	Real-time detection capability simplicity and adaptability to various datasets	May require substantial computational resources; further validation needed for generalizability	A neural network-based approach using LSTM for thermal fault detection in LIBs	[14]
Combines meta-learning with deep learning techniques for estimating SOC of Li-ion batteries	Achieves significantly lower SOC estimation errors compared to traditional transfer learning methods	Limited scalability and generalizability; may require a large amount of training data	Demonstrates potential for practical applications and promise in enhancing battery health monitoring and management	[23]
Least-Squares GAN and Gated Recurrent Unit	Uses GAN and GRU for more accurate RUL predictions; applies larger penalties to larger errors	May have limitations in handling complex data scenarios	Offers potential for improving RUL prediction accuracy but may require further investigation for scalability and effectiveness across different LIB systems and conditions	[25]
Employed GANs for data augmentation in health prediction	Addresses the challenge of sparse data improves accuracy of battery state estimation models	Extensive computational resources may be needed specific data requirements	Augmented LIB data for better health prediction with GANs	[26,29]
Bidirectional LSTM with Attention Mechanism for SOH Estimation	Improved SOH estimation accuracy; robust feature selection	Computational demands; potential generalizability concerns	A model integrating bidirectional LSTM with attention mechanism for SOH estimation	[27]
Backtracking Search Algorithm (BSA) Optimized Back-propagation Neural Network	Enhances SOC estimation accuracy for LIBs in EVs; shows effectiveness in various driving profiles and temperature conditions	May not be suitable for all battery chemistries; requires a considerable amount of training data	Offers potential for improving SOC estimation accuracy but needs further validation for generalizability and adaptability	[32]

Table 2. *Cont.*

Investigation/Methods	Advantages	Disadvantages	Contribution	Ref.
Self-supervised learning framework for SOH estimation in LIBs for EVs reduces labeled data reliance	Efficient SOH estimations across LIB chemistries	Sole focus on SOH excludes SOC estimation	Improves EV battery management efficiency safety and longevity	[33]
Deep Learning-based Transformer model trained with Self-Supervised Learning (SSL) improves SOC prediction in LIBs for EVs even in varying temperatures	Transformer captures long-range dependencies SSL reduces labeled data reliance	Focus on EVs resource-intensive	Enhances SOC accuracy and robustness in EVs reducing labeling requirements	[34]
DL-based transformer model for SOC estimation in LIBs for EVs with SSL training high accuracy	Low RMSE MAE; SSL reduces labeled data reliance	Focus on EVs computational demands	Enhances SOC estimation accuracy reliability efficiency and adaptability in EVs	[34]
Dual Neural Network Fusion Model for SOC Estimation	Accurate SOC estimations under various conditions	Requires dynamic stress test (DST) data for training; may not be universally applicable	A model using a combination of linear neural networks and backpropagation neural networks for SOC estimation in LIBs	[37]
Deep Reinforcement Learning (DRL) for LIB Degradation Cost Estimation	Robust Control Strategy: DRL approach ensures energy arbitrage actions do not harm LIB health by comprehending the inherent uncertainty in LIBs' degradation patterns	Computational Complexity: High computational resources may be necessary for training and forecasting	Implementation of a DRL approach for estimating the degradation cost of LIBs to optimize their participation in the energy arbitrage market	[38]
Introduces a multi-task learning network	Impressive accuracy and efficiency compared to other multi-task learning models	Specific data requirements potential challenges in real-world implementation and validation	Efficient SOC and SOE estimation with MTL	[40]
Developed a multi-task learning framework	Robust performance and superiority over single-task learning methods	Extensive computational resources may be needed	Robust capacity and power degradation prediction	[39,40]
Develops a scalable and robust method for estimating the remaining capacity of LIBs solely based on data	Improves the accuracy and efficiency of SOH estimation for LIBs	Requires a large amount of historical data for training	Represents a significant advancement in estimating the remaining capacity of LIBs and enhances battery management and forecasting systems	[39,40]
Proposes a cloud-based AI-enhanced framework for co-estimating SOC and SOH	Shows potential for enhanced battery management and performance forecasting	May have computational demands and may not be universally applicable	Offers potential for improving battery management but may require careful consideration of computational resources and applicability	[41]
Leveraged quantum assimilation for SOH prediction	Refines SOH prediction provides insights into complex battery behaviors	Extensive computational resources may be needed specific data requirements	Improved SOH prediction with quantum assimilation	[43]
Introduces a sophisticated battery digital twin framework	Offers a comprehensive representation of battery behavior over time with high accuracy and compatibility with onboard execution	Requires a large amount of historical data for training	Represents a significant advancement in real-time battery modeling with potential applications in EVs and energy storage systems	[48,49]
Graph Neural Network (GNN) for Capacity Estimation	Robust Adaptability: Utilizing neural architecture search for selecting optimal operations improving model adaptability	Data Demands: May require substantial data for training to maintain optimal model performance	Utilization of a GNN to estimate LIB capacity by integrating diverse sensor measurements into a graph-like structure	[62]
Physics-Informed Neural Networks (PINNs) to accurately predict LIBs' temperature without requiring extensive training data or explicit physics equations	Accurate prediction of LIBs' temperature without needing extensive training data or explicit physics equations	May not be as accurate as methods that utilize more data	Offers a method that does not require extensive training data or explicit physics equations for accurate LIBs' temperature prediction	[64]

Table 2. *Cont.*

Investigation/Methods	Advantages	Disadvantages	Contribution	Ref.
Proposed a method using transferred CNN for state monitoring	Superior accuracy and computational efficiency across diverse application scenarios	Extensive computational resources may be needed specific data requirements challenges in real-world implementation and validation	Superior state monitoring using transferred CNN	[65]
Developed a framework combining transfer learning and network pruning to create streamlined CNN models for improved estimation performance	Combines transfer learning and network pruning to create streamlined CNN models with enhanced estimation performance	May require a large source dataset for pre-training	Develops a framework that improves CNN models' estimation performance by combining transfer learning and network pruning	[67]
Combined time-frequency image (TFI) analysis with a transfer deep learning algorithm to diagnose degradation of LIBs	Uses time-frequency image (TFI) analysis and a transfer deep learning algorithm for accurate LIBs' degradation diagnosis	May require more computational resources	Proposes a methodology that improves LIBs' degradation diagnosis through TFI analysis and transfer deep learning	[67]
Focused on predicting SOH in LiBs through transfer learning to address limited training data	Addresses the issue of limited training data by utilizing transfer learning for SOH prediction in LiBs	May have limitations in scenarios where there is not a strong foundation for transfer learning	Focuses on predicting SOH in LiBs and offers a method that overcomes the limitations of training data by integrating knowledge from one task to improve predictions in a related task	[68]
Deep Domain Adversarial Network	Uses adversarial training and unsupervised feature alignment metrics potentially improving SOH estimation accuracy for real-world applications	May require substantial computational resources and may have limitations in handling complex data scenarios	Shows promise in improving SOH estimation but requires further investigation for scalability and effectiveness across different LIB systems and conditions	[68]

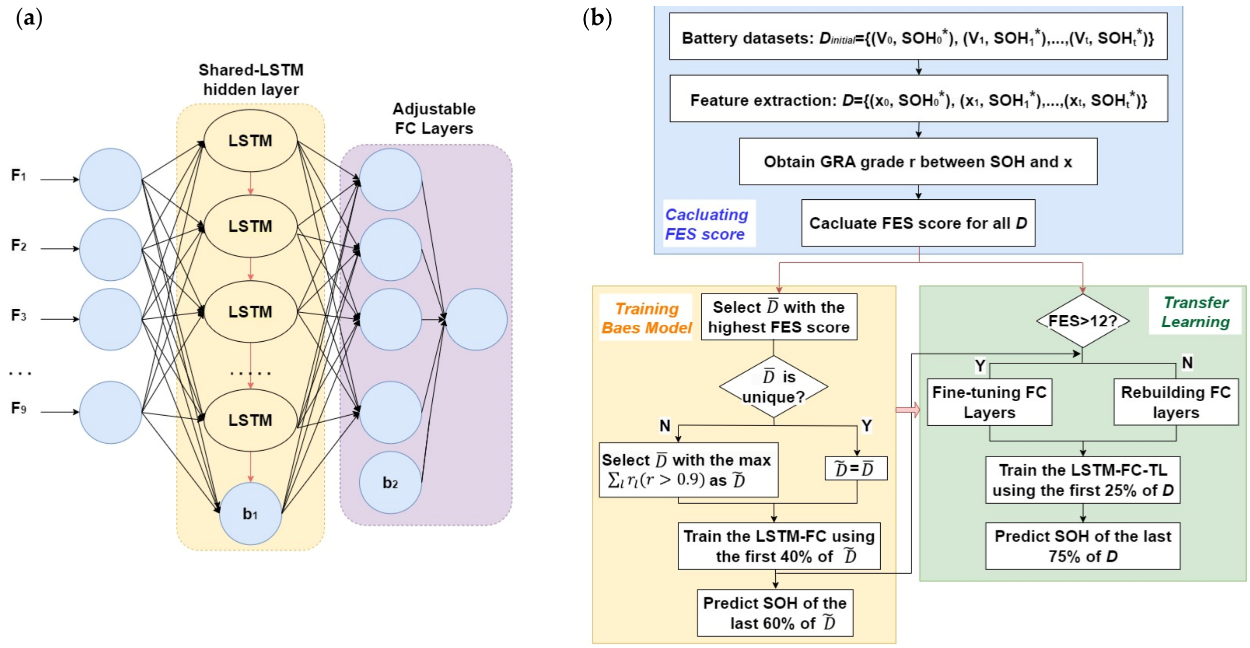

Figure 14. (**a**) The architecture of LSTM-FC. During transfer learning, the LSTM was frozen as shared hidden layer, but the FC layers were set to be adjustable to learn private properties for different LIBs. (**b**) The flowchart of the proposed SOH prediction method for LIBs based on transfer learning. The LSTM-FC is the base model, and LSTM-FC-TL denotes the transferred base model. The task $\overline{D}$ with highest FES score is selected as the best representative task $\widetilde{D}$ to train the base model [68].

6. Other Models and Techniques

6.1. Energy-Based Models

In LIB health monitoring (BHM), accurately estimating the SOH is a significant challenge, particularly when complete discharging curves are not readily available [46]. Address this issue by exploring energy-based features for precise and reliable SOH estimation, recognizing that incomplete discharging conditions often disrupt the accuracy of conventional aging features extracted from full cycle processes. Their Enhanced Gaussian Process Regression (GPR) model introduces several enhancements, including features from direct measurement curves, a multidimensional linear mean function, and a novel covariance function designed to adapt to data fluctuations. Experiments conducted on batteries from the NASA dataset with varying initial health states demonstrate the model's effectiveness and superior performance, with a mean root mean squared error (RMSE) of only 0.97% in the testing set. This research represents a significant step forward in battery health estimation, particularly under incomplete discharging conditions, and holds promise for more precise SOH monitoring in lithium-ion BHM.

As shown in Figure 15. Cai et al. [69] have devised an innovative approach that leverages energy-based features and an enhanced GPR model to tackle the challenge of accurate SOH estimation under incomplete discharging conditions. Their model's strong performance and ability to outperform other methods highlight its potential for enhancing LIB health monitoring and management [69].

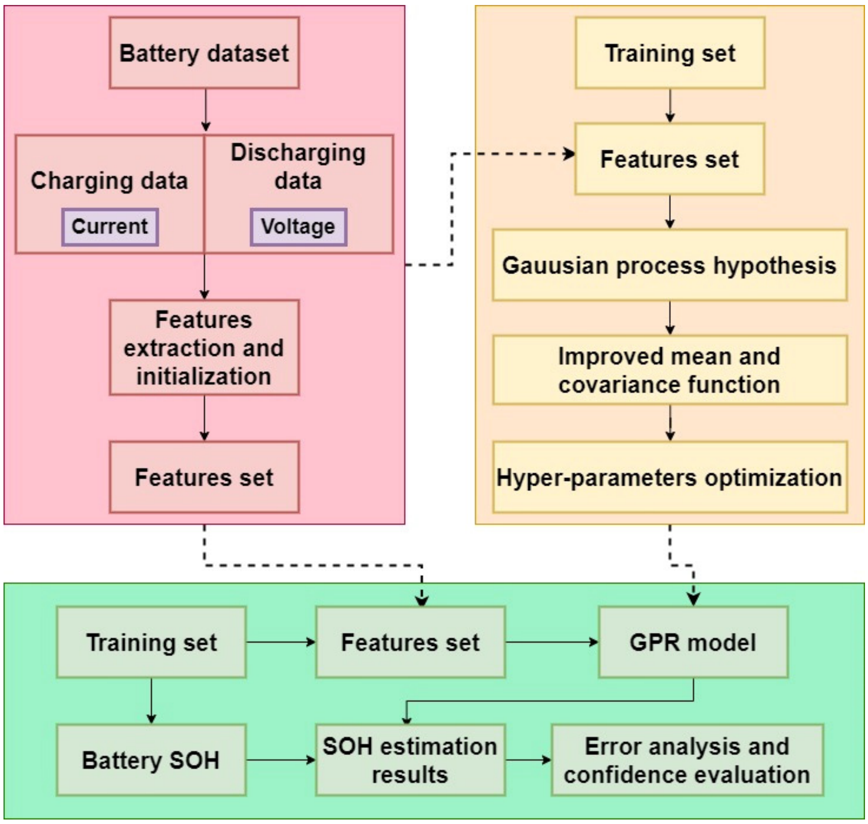

Figure 15. The framework of the Cai et al. model for LIBs SOH estimation [69].

6.2. Discussion

Table 3 discusses the significance of accurate state-of-health (SOH) estimation for LIBs, especially in the context of EVs and consumer electronics. It highlights the challenges associated with forecasting SOH and RUL and the role of machine learning (ML) in addressing these challenges. In addition, it delves into a more comprehensive explanation of different key points.

Table 3. Significance of accurate SOH estimation for LIBs.

Applications	Description	Ref.
Advancements in Battery Technology	Over the past decade, there have been significant strides in battery technology, with a notable focus on LIBs. These advancements have played a crucial role in revolutionizing the development of EVs and other technologies that depend on efficient energy storage.	He et al. [70]
Importance of SOH Estimation	Precise estimation of the state-of-health (SOH) in LIBs holds paramount importance. The SOH serves as a measure of a battery's health and condition, significantly influencing its reliability, safety, and long-term cost-effectiveness.	Wang et al. [71]
Challenges in SOH and RUL Forecasting	Despite notable technological progress, accurately forecasting the state-of-health (SOH) and RUL of Li-ion batteries poses a considerable challenge. This limitation serves as an impediment to the advancement of technologies such as EVs and consumer electronics.	Xia et al. [72]
Consumer Electronics and LIBs	LIBs are extensively utilized in diverse consumer electronic devices, playing a vital role in the expansion of industries associated with smartphones, laptops, and other portable devices. Safeguarding the health of these batteries is imperative to mitigate safety concerns, such as the risk of explosions or fires.	Arora et al. [73]
Capacity Prediction Techniques	Conventional methods for predicting battery capacity frequently depend on extracting features from measured signals acquired under specific operating conditions. However, these approaches may not consistently deliver accurate predictions across all scenarios.	Peng et al. [74]
Monitoring SOH in EVs	Monitoring the state-of-health (SOH) of electric vehicle (EV) batteries poses specific challenges due to the labor-intensive and time-consuming processes involved in battery cycling and capacity measurements necessary for creating precise SOH estimation models.	Shah et al. [75]
RUL Prediction	Precise forecasting of the RUL of LIBs is essential for extending battery lifespan and ensuring safety. Nevertheless, the limited number of charge and discharge cycles in LIBs may require additional historical data to enhance prediction accuracy.	Yao et al. [76]
Degradation in LiBs	LIBs experience degradation over time due to factors such as usage and exposure to environmental conditions. This degradation affects their energy storage capacity and power supply capability, posing a challenge for accurate prediction.	Kabir et al. [77]
Machine Learning in LIB State Estimation	Machine learning (ML) techniques have become increasingly popular in various fields, including LIB state estimation. These ML methods are employed to improve the accuracy of predicting the state of LIBs while simultaneously reducing the computational burden.	Chandran et al. [78]
Balancing Factors in LIB Design	The design of LIBs requires a delicate balance of multiple factors, encompassing chemistry, materials, and manufacturing processes. Effectively achieving accurate state estimation while considering these intricacies poses a challenge.	Iraola et al. [79]

The accurate estimation of the state-of-health and RUL of LIBs is crucial for the safety, reliability, and longevity of batteries used in EVs and consumer electronics. While challenges exist, machine learning offers a promising avenue for improving the accuracy of these predictions and addressing the complexities inherent in battery design and operation. Table 4 provides a range of topics related to the implementation of AI in various aspects of battery management and energy storage systems. In addition, it breaks down and provides more comprehensive explanations for each of the different topics. Table 5, demonstrate deep learning methods for health monitoring of LIBs.

Over the past decade, there have been significant advancements in battery technology, particularly in the context of LIBs, which have revolutionized the development of electric vehicle (EV) technologies. These advancements have opened up new possibilities for clean and sustainable transportation. One critical aspect of the effective use of LIBs is accurately estimating their state-of-health (SOH). The SOH of a battery is a measure of its overall condition and performance and is vital to ensuring the reliability, safety, and cost-effectiveness of LIBs over the long term. Accurate SOH estimation is particularly crucial in applications like EVs, where battery failure can have significant safety and economic consequences.

Table 4. The implementation of AI in various aspects of battery management.

Applications	Description	Ref.
Machine Learning Applications in Property Prediction	Machine learning is employed to predict various properties of materials, and this includes properties of materials utilized in batteries, such as capacity, conductivity, or thermal properties.	Hu et al. [6]
Online Health Diagnostics for LIBs	AI is employed for real-time diagnostics of battery health, particularly in EVs, utilizing data from both cloud and edge computing. Ensuring the accuracy and robustness of these diagnostics is crucial for effective battery management.	Tian et al. [7]
Modeling Multiphysics and Multiscale Electrochemical Systems	This encompasses the intricate process of employing AI to model and predict electrochemical systems in batteries, often necessitating complex calculations for accurately simulating these systems.	Fu et al. [8]
State-of-Health (SOH) Estimation for LIBs	State-of-health (SOH) estimation is crucial for evaluating the health and reliability of LIBs over time. It provides insights into how well a battery can perform in comparison to its original condition.	Liang et al. [9]
Battery State Prediction	Forecasting the state of batteries, such as the SOC, is essential for ensuring safe and efficient operation, particularly in EVs. This helps prevent issues like unexpectedly running out of power.	Liu et al. [10]
Integrated Framework for AI in Battery Management	An integrated framework likely denotes a comprehensive approach to integrating AI into battery management systems, wherein various AI techniques and components collaboratively function seamlessly.	Shi et al. [11]
Deep Learning in SOH Estimation	Deep learning techniques, such as CNN and recurrent neural networks (RNNs), are applied for state-of-health (SOH) estimation. Nevertheless, there might be untapped potential in these methods that warrants further exploration.	Wang et al. [13]
LIBs Capacity Estimation	Precisely estimating the capacity of LIBs is crucial for effective management. AI, particularly CNN, is being investigated for this task, although the challenge of data collection persists.	Tian et al. [15]
Correlation Among Features in Predictive Models	Identifying and leveraging correlations among features can enhance the accuracy of predictive models for battery-related tasks. This, in turn, can result in more efficient and reliable predictions.	Zhang et al. [16]
Distribution Discrepancies in Training and Testing Data	This pertains to the challenge of ensuring that AI models trained on one dataset can effectively generalize to different working conditions or datasets.	Xie et al. [17]
Data-Driven Fault Prediction	AI is utilized for predicting faults or issues in batteries. Continual learning is being explored as a method to adapt models to changing operational or environmental conditions.	Marri et al. [18]
Single-Scale Feature Limitations	Challenges emerge when attempting to predict the health of batteries, attributed to factors such as capacity regeneration and random fluctuations. These elements can restrict the accuracy of predictions based on single-scale features.	Bao et al. [19]
Temperature Monitoring of LIBs	Monitoring the temperature of LIBs is essential for both their performance and safety. AI techniques, such as convolutional transformers, are applied for multi-step time series forecasting of temperature in this context.	Wan et al. [20]
Battery Discovery and Electrolyte/Electrode Materials	AI is utilized to explore and identify new battery materials, encompassing both electrolyte and electrode materials. This application contributes to the development of more efficient and durable batteries.	Zhang et al. [22]
Challenges in Deploying AI in Real-World Scenarios	Despite the promise of AI in battery management, implementing it effectively in real-world scenarios poses significant challenges. These challenges may encompass issues such as data availability, computational resources, and model robustness.	Zhao et al. [31]
Spiking Neural Networks (SNNs)	Spiking Neural Networks (SNNs) are a type of neural network inspired by the human brain. They are being explored as an energy-efficient alternative for specific battery-related tasks.	Hannan et al. [32]
Transfer Learning for Digital Battery Twins	Transfer learning is a technique wherein pre-trained models can be adapted for new tasks. In the realm of battery management, this approach can save time in training models for different battery aging states.	Hannan et al. [34]
AI Implementation in Battery Management	This pertains to the application of AI techniques for optimizing and managing batteries, especially in EVs and grid energy storage systems. AI has the potential to improve battery performance, extend longevity, and enhance safety.	Che et al. [41]
Regression GAN	GANs are employed to create models capable of generating data that closely resembles real-world data. In this context, GANs are utilized to develop models for batteries, taking into account factors such as noise and sensor failures.	Zhao et al. [44]

Table 5. Deep learning methods for health monitoring of LIBs.

Method	Purpose	Advantages	Considerations	Ref.
Auto-encoders	Detecting deviations from normal battery behavior.	Can identify anomalies without explicit labels.	Requires a well-defined definition of normal behavior	Hu et al. [6]
Recurrent Neural Networks (RNNs), particularly LSTM networks	Predicting SOC and SOH over time.	Effective for handling sequential battery data.	Requires time-series data and may need significant training data	Che et al. [33]
Gated Recurrent Units (GRUs)	Analyzing voltage, current, and temperature time-series data.	Suitable for capturing temporal dependencies.	Data quality and preprocessing are crucial	Liu et al. [56]
CNN	Analyzing microscopic images for defect detection	Effective for image-based monitoring	Requires image data and specialized hardware for image capture	He et al. [70]
Multimodal Deep Learning	Combining data from various sensors	Provides a holistic view of battery health	Requires synchronization and alignment of diverse data sources	Garcia-Ceja et al. [80], Gaw et al. [81]
Transfer Learning with pretrained models	Fine-tuning models for battery health tasks	Can leverage pretrained knowledge and require less labeled data	Domain adaptation may be needed	Ni et al. [82], Ma et al. [83]
Reinforcement Learning (RL) agents	Optimizing battery management decisions	Can learn to maximize battery lifespan and performance	Complex to implement and may require simulation environments	Li et al. [84], Subramanya et al. [85]
Interpretable Models alongside deep learning	Providing insights into model decisions	Ensures transparency and understanding of AI-driven decisions	May involve trade-offs between accuracy and interpretability	Zhao et al. [86], Ying et al. [87]
Models adapted to streaming data	Real-time monitoring and decision making	Immediate responses to changing battery conditions	Resource-intensive and requires continuous data streaming	Liu et al. [88], Li et al. [89]
Synthetic data generation, e.g., GANs	Augmenting limited training datasets	Increases robustness and generalization	Requires additional computational resources for data generation	Naaz et al. [90]

Accurate SOH estimation is a challenging task that has far-reaching implications. It is not limited to EVs but also extends to the broader use of LIBs in consumer electronic devices. In the context of consumer electronics, monitoring the health of LIBs becomes crucial because any potential instability in these batteries can lead to dangerous incidents such as explosions or fires. Traditionally, techniques for predicting the capacity (the amount of energy a battery can store) of LIBs have relied heavily on analyzing features extracted from measured signals obtained under strict operating conditions.

Predicting the SOH of LIBs, especially in the context of electric vehicle batteries, is particularly challenging due to the time-consuming and labor-intensive process involved in battery cycling and the capacity measurements needed to create an accurate SOH estimation model. Furthermore, accurately forecasting the RUL of LIBs is essential for extending battery lifespan and ensuring safety. However, due to the limited number of charge and discharge cycles that LIBs can undergo before they degrade significantly, having sufficient historical data is a major challenge that can impact the accuracy of these predictions.

LIBs naturally degrade over time due to usage and exposure to environmental conditions. This degradation affects their ability to store energy and deliver power effectively. Accurately predicting the capacity and power fade of LIBs cells is especially challenging because of the inherent manufacturing variations in battery cells and the complex nonlinear aging processes they undergo.

Given the importance of accurate LIBs state estimation, it has become an area of great interest for researchers. However, designing LIBs involves balancing multiple factors, such as energy density, safety, and cost-effectiveness, making it a complex task. To address these challenges, machine learning (ML) has gained prominence as a tool to improve the accuracy of LIB state estimation. ML techniques can handle large datasets and complex patterns in data, thus aiding in more precise predictions while reducing the computational burden on researchers. Table 6 demonstrates key features for transformer-based models for LIB health prediction and state estimation. A categorization and summary of the key insights and implications of different methods for health monitoring and state estimation in LIB is shown in Table 7.

Table 6. Transformer-based Models for LIB health prediction and state estimation.

Key Features	Description
Improved Accuracy:	Transformer-based models are proficient at forecasting RUL, SOH, and SOC. Transformer-based models consistently exhibit enhanced precision when predicting RUL, SOH, and SOC in LIBs. These models are adept at capturing temporal patterns and extracting features from sequential data, resulting in more dependable predictions.
Noise Reduction:	Integrating Denoising Auto-encoders (DAE) diminishes the influence of noise. The integration of Transformer-based models with preprocessing methods such as Denoising Auto-encoders (DAE) proves effective in minimizing the impact of noise on battery capacity data, leading to increased accuracy in predictions.
Advanced Features:	Performance is boosted through feature extraction from EIS data and the utilization of VITs. The enhancement of LIB health prediction models is achieved by incorporating sophisticated features and techniques, including the extraction of features from EIS data and the integration of VITs.
Simplicity and Scalability:	Innovative equalizer designs streamline battery management. The simplification of battery management is facilitated by novel equalizer designs, which eliminate the necessity for intricate control strategies. This results in reduced system costs without compromising efficiency.
AI Integration:	Self-attention and autoregression enhance prediction accuracy. The integration of AI techniques such as self-attention and autoregression not only improves prediction accuracy but also holds the potential to revolutionize LIB health prediction.
Multiphysics and Multiscale Systems:	Cloud-based AI-enhanced frameworks for jointly estimating SOC and SOH. The implementation of cloud-based AI-enhanced frameworks for the simultaneous estimation of SOC and SOH in multiphysics and multiscale LIB systems shows potential for improving battery management and forecasting performance under realistic operational conditions.

CNNs have demonstrated effectiveness in monitoring battery health through image-based analysis. This includes tasks such as examining electrode microstructures and detecting damage in separators [91].

LSTM networks [92] are well-suited for analyzing time-series data, making them suitable for monitoring battery discharge and charge cycles. In contrast, recurrent neural networks (RNNs) [93] are beneficial for analyzing sequential data, enabling the prediction of battery degradation, SOC, and SOH by analyzing historical data.

Auto-encoders, as unsupervised deep learning models, can be employed for feature extraction and the detection of anomalies [94]. They excel at identifying subtle changes in battery behavior and anomalies in voltage, current, or temperature data.

Reinforcement learning (RL) techniques [95] can be utilized to optimize battery management and control strategies, extending battery life by adapting charging and discharging policies based on real-time battery health and usage patterns.

Hybrid models, which integrate various deep learning methods, show promise for enhancing overall performance [96]. These models leverage the strengths of different deep learning techniques, such as CNNs for image analysis and LSTMs for time-series data, providing a comprehensive perspective on battery health.

7. Navigating Challenges in LIB Health Prediction

This section explores the intricate challenges associated with accurately predicting the state-of-charge (SOC) and state-of-health (SOH) of LIBs for EVs. The discussion encompasses various aspects, including multiphysics modeling, deep learning for SOH estimation, online diagnostics, capacity estimation, data-driven methods, temperature monitoring, alternative approaches, correlation challenges, distribution discrepancies, fault prediction, and advanced techniques. The narrative underscores the potential of innovative solutions, emphasizing the impact of advanced techniques on practical applications in EVs and energy storage systems. The accompanying table highlights some features related to advancements in LIB health prediction.

Challenges in Battery Modeling: Precisely estimating the state-of-charge (SOC) of batteries is vital for ensuring the safe and efficient operation of EVs, particularly in complex loading scenarios. Accurate modeling and forecasting of multiphysics and multiscale electrochemical systems under realistic conditions using first-principles and atomistic calculations have presented challenges [97].

State-of-health (SOH) Estimation: The accurate estimation of the state-of-health (SOH) in LIBs is crucial for ensuring the safety and reliability of EVs. Deep learning for SOH estimation has mainly relied on CNNs and recurrent neural networks (RNNs), not fully exploiting the method's potential. Transfer-learning could be employed in the training process of digital battery twins to enhance data and computational efficiency [98,99].

Online Health Diagnostics: The application of deep learning in LIB online health diagnostics, using cloud and edge computing with big data, has seen widespread implementation. Challenges include improving diagnostics' accuracy, robustness, and real-time applicability, particularly considering degradation feature trajectories' differences between training and testing domains [100,101].

Capacity Estimation: Online estimation of LIBs capacity is crucial for LIBs management systems in EVs and grid energy storage applications. CNNs show promise in this task, but collecting aging data is time-consuming and costly [102,103].

Data-Driven Methods and Challenges: Accurate SOH estimation using data-driven methods is challenging due to the difficulty of measuring real SOH during actual LIBs operation and noise or sensor failures. Regression GAN could be used to develop a general model for batteries [104].

Temperature Monitoring: Monitoring the temperature of LiBs is crucial for improving performance and mitigating the risk of TR. A convolutional transformer (Convtrans) could be used for multi-step time series forecasting [105,106].

Alternative Approaches: spiking neural networks (SNN) present an alternative to traditional artificial neural networks, known for their excellent simulation of spatiotemporal feature learning abilities and low power consumption [107].

Table 7. Advancements in LIB Health Prediction [108].

Key Features	Perspectives
Practical Applications	The combined results underscore the significant influence of advanced techniques on predicting the health of LIBs, positioning them as promising candidates for practical applications in EVs and energy storage systems.
Effectiveness of Advanced Techniques	Research indicates the efficacy of transformer-based models, particularly when integrated with preprocessing methods like DAE, EIS data analysis, and innovative cell equalizers. The incorporation of cloud-edge computing and advanced deep learning techniques, such as self-supervised transformer neural networks, holds promise for tackling complexities in multiphysics and multiscale systems.
Advanced Techniques for Prediction	Transformer-based models and bidirectional encoder representations from transformers (BERT) are emphasized for their role in improving the prediction of LIB health and state estimation. These techniques exhibit promise in tackling challenges associated with RUL, SOH, and SOC prediction for LIBs.
Challenges in Fault Prediction	The early prediction and thorough comprehension of faults in LIBs could markedly enhance product quality. Continual learning holds the potential for flexibility by adapting previously acquired knowledge to new tasks.
Distribution Discrepancies and Generalization	Numerous existing methods operate under the assumption that training and testing data adhere to the same distribution. This can result in models that prove ineffective when applied to datasets operating under distinct working conditions.
Correlation and Feature Aggregation	Current prediction methods frequently fall short in uncovering correlations among features, thereby affecting the accuracy of predictive models. Identifying these correlations can assist in recognizing features with high similarities, enabling their aggregation to enhance the accuracy of predictive models.

8. Determination of Battery Parameters in EVs

Analytical Models: Engineers frequently employ mathematical models to simulate the behavior of LIBs, which are extensively used in EVs and energy storage systems (ESS). These models account for variables such as cell chemistry, temperature, charging/discharging rates, and the impacts of aging. Some popular models include the equivalent circuit model, which represents the battery as an electrical circuit with resistors, capacitors, and voltage sources; the Doyle–Fuller–Newman (DFN) model, which considers electrochemical reactions within the battery; and the pseudo-2D and 3D models, which offer more intricate representations of the battery's inner workings [109].

Empirical Data: Battery manufacturers and researchers often conduct experiments to assess the performance of LIBs under varying operational conditions, such as charge/discharge cycles, temperature fluctuations, and aging. By scrutinizing this experimental data, engineers can determine critical parameters like capacity, voltage, internal resistance, and self-discharge rate [110].

Real-Time Monitoring: Modern EVs and ESS commonly include battery management systems (BMS) that monitor each battery cell's SOC, SOH, and state of function (SoF). The BMS utilizes sensors and algorithms to estimate parameters such as SoC (the remaining percentage of a full charge), SoH (the overall condition of the battery and its remaining lifespan), and SoF (the battery's power delivery capabilities under different conditions). Advanced BMSs might also incorporate machine learning algorithms to enhance the accuracy of these estimations over time by analyzing real-world data [111].

AI and Machine Learning: AI and ML techniques are increasingly utilized to optimize battery performance and enhance battery management strategies. For instance, reinforcement learning algorithms can learn optimal charging and discharging strategies to minimize degradation and improve efficiency. Predictive maintenance algorithms can also forecast potential battery failures and suggest preemptive measures. AI and ML methods can likewise enhance the accuracy of analytical models and empirical data by identifying patterns and correlations within extensive datasets.

It is important to note that battery technology and methodologies for determining battery parameters are continually evolving, and new AI and ML-based techniques are likely to emerge in the future. As of my last update, AI and ML applications were not yet widely integrated into commercial EVs and ESS, but ongoing research and development in this domain was occurring [112,113].

Vinay Vakharia et al. [114] introduced an enhanced explainable AI (Ex-AI) framework designed for forecasting battery discharge capacity. Figure 16 illustrates the Ex-AI methodology to estimate Li-ion battery discharge capacity. Initially, three deep learning (DL) models, namely stacked LSTM networks (stacked LSTMs), GRU networks, and stacked recurrent neural networks (SRNNs), were constructed using six input features. Ex-AI was utilized to discern pertinent features and optimize its operational parameters, leveraging the jellyfish metaheuristic optimization technique. The findings indicate that employing the jellyfish-Ex-AI model resulted in superior discharge capacity predictions. Remarkably low RMSE of 0.04, mean absolute error (MAE) of 0.60, and MAPE of 0.03 were achieved with the Stacked-LSTM model, underscoring the efficacy of our proposed methodology.

Su et al. [115] introduced a deep learning neural network and a fine-tuning-based transfer learning approach aimed at precise and robust SOH estimation for diverse battery types. Figure 17 illustrates the procedures to build an ML-based SOH estimation method. Firstly, they proposed a universal high-frequency (HF) extraction method to derive four highly relevant HFs. Subsequently, they constructed a deep learning neural network incorporating LSTM and fully connected layers to model the correlation between the HFs and SOH. Thirdly, they employed a fine-tuning-based transfer learning strategy for SOH estimation across different battery types. Their proposed methods were thoroughly evaluated using three open-source datasets. Experimental findings indicate that the deep learning neural network, coupled with the HFs, accurately estimates SOH within a single dataset, yielding a mean absolute error (MAE) and RMSE of 1.21% and 1.83%, respectively, without resorting to the transfer learning strategy. Moreover, for transfer learning across various aging datasets, the overall MAE and RMSE are restricted to 1.09% and 1.41%, underscoring the efficacy and reliability of the fine-tuning strategy.

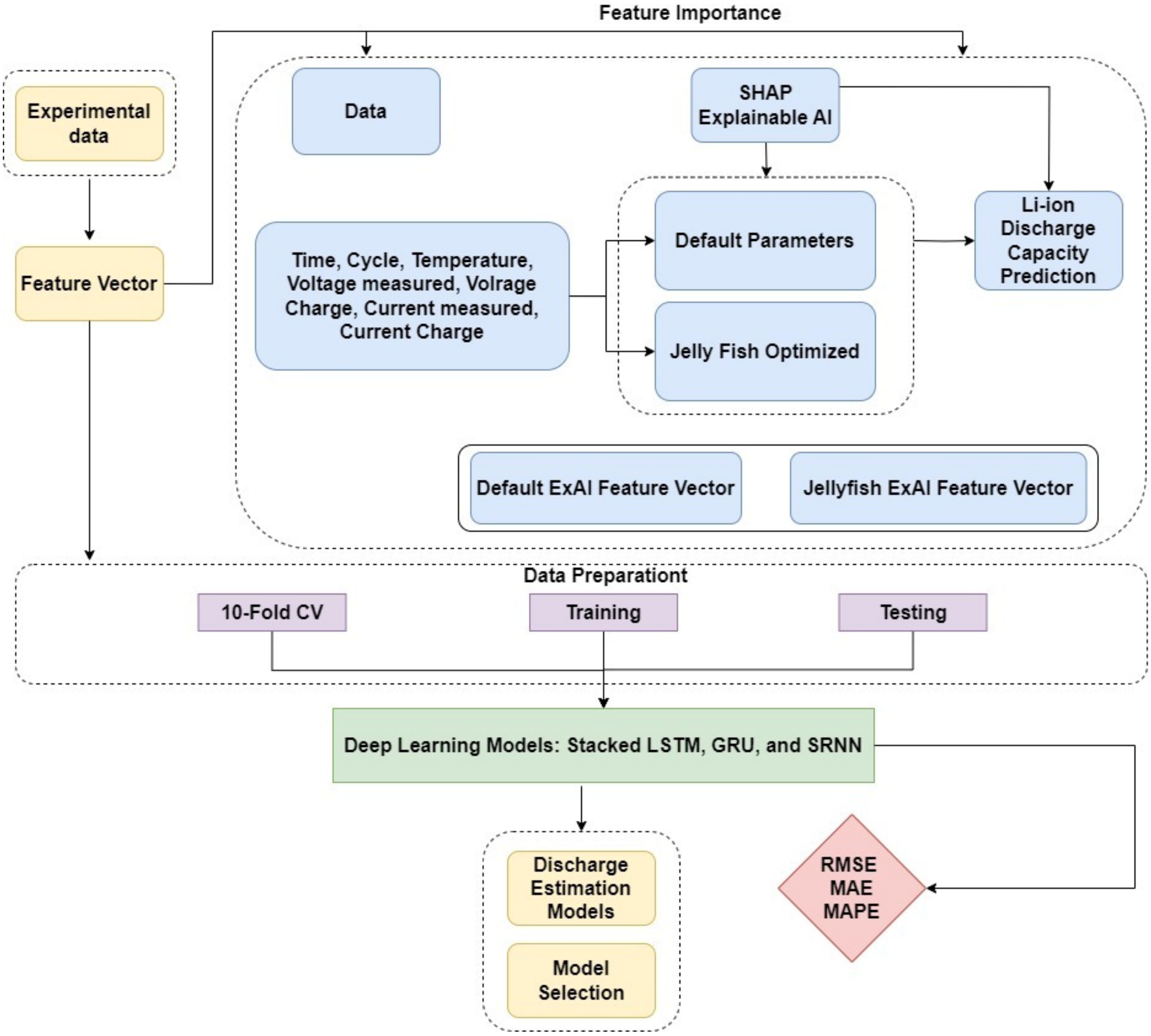

Figure 16. Ex-AI methodology to estimate Li-ion battery discharge capacity.

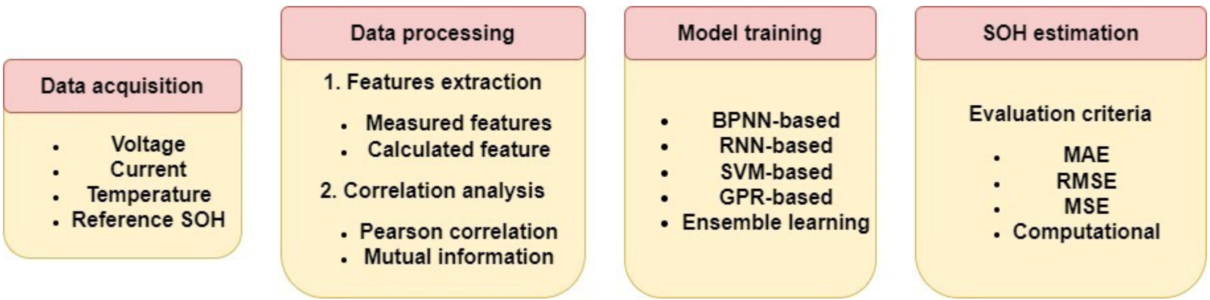

Figure 17. The procedures to build an ML-based SOH estimation method.

9. Estimating the Health of LIBs under Dynamic Conditions

Electrochemical Impedance Spectroscopy (EIS)

Xiong et al. [116] discussed the significance of efficiently estimating the health state of LIBs for performance monitoring and economic evaluation. It emphasizes the challenge of online health state estimation and highlights the use of data-driven techniques, particularly artificial neural networks (ANNs) like the Elman neural network (ENN). The paper proposes an improved ENN method, called the EIS-CS-ENN model, utilizing EIS and cuckoo search (CS) algorithms. Comparative analysis demonstrates the superiority of the EIS-CS-

ENN model over other ANN methods. It stresses the importance of selecting appropriate health indicators (HIs) for efficient state estimation and presents evaluation results and suggestions based on mathematical modeling and state requirements. Additionally, the robustness of the EIS-CS-ENN model for LIB health state estimation is verified.

Li et al. [117] addressed the challenge of assessing the SOH of LIBs for second-life (SL) applications without intrusive testing. They proposed using experimental EIS data and neural networks (NN) to evaluate SoH, along with a novel dimensionality reduction approach to streamline EIS measurements. Validation with datasets of LiBs under SL conditions shows promising results, with low RMSEs obtained for both lithium iron phosphate (LFP) and lithium nickel manganese cobalt (NMC) cells. The proposed methodology offers advantages over conventional capacity tests, including non-invasiveness, shorter processing time, and lower energy consumption, thus facilitating the SL market for retired LiBs.

Wang et al. [118] addressed the challenge of accurately estimating the SOH for LIBs due to their complex degradation mechanisms. It proposes an EIS-based method that combines an improved equivalent circuit model (ECMC) with data-driven techniques. By identifying parameters from EIS data and using them as inputs for gaussian process regression (GPR), the proposed method achieves accurate SOH estimation with an average RMSE of only 1.77%. This approach demonstrates promising results even under different temperatures, indicating its effectiveness in estimating LIBs' SOH.

10. Voltage and Current Profiling

Li et al. [119] introduced a method for estimating the SOH of LIBs based on their constant-current charging curve, aiming to improve both the accuracy and stability of the estimation. It utilizes a multi-objective optimization extreme learning machine (MOWOA-ELM) approach, where a logit polynomial fitting model is employed to extract relevant features from the charging curve. The MOWOA-ELM model, optimized using a modified whale search algorithm, achieves low RMSE (0.43%) and standard deviation (0.28%) in SOH assessment. Experimental results validate the effectiveness and feasibility of the proposed framework.

Ko et al. [120] addressed the lack of exploration into constant voltage (CV) charging for LIBs compared to constant current (CC) charging. It introduced the concept of the differential current curve (dQ/dI curve) in CV charging and utilized it as a feature to identify battery states. Through qualitative interpretation with an equivalent circuit model and fitting with Gaussian process regression (GPR), the relationship between dQ/dI values and battery states is established. Using 4836 sets of CV charging data, the paper achieves excellent SOH estimation with a mean absolute error (MAE) of 0.18%. Additionally, a novel experimental approach for SOC estimation is introduced, reducing SOC prediction MAE to about 0.88%. These findings suggest that the dQ/dI curve is a promising tool for accurate battery state estimation.

11. Coulomb Counting

Das et al. [121] emphasized precise state-of-charge (SOC) estimation for electric vehicle dashboards, utilizing battery modeling and parameter estimation for lithium-iron-phosphate (LFP) batteries. It introduces a modified Coulomb counting (CC) method and validates the battery modeling by comparing it with physical battery terminal voltage profiles. The approach aims to improve initial SOC determination and enhance overall accuracy in SOC estimation for EVs.

Li et al. [122] proposed a model-based fault diagnosis algorithm to address challenges in real-time SOC estimation for LIBs using Coulomb counting. This algorithm effectively diagnoses three typical faults without extra measurements or prior battery knowledge. It can be implemented intermittently or remotely alongside Coulomb counting to ensure real-time estimation. Experiments validate the algorithm's effectiveness, achieving 100% true-positive rates in diagnosing faults.

12. Kalman Filtering and State Estimation

Wu et al. [123] proposed an improved particle filter-based method for accurately estimating battery parameters and state values to prevent overcharge and discharge accidents. The method incorporates unscented transformation and multi-innovation techniques to optimize particle distribution and update status values. It jointly estimates battery SOC and SOH by considering parameter variation over different time scales. Experimental validation demonstrates the algorithm's high accuracy in real-time SOC and SOH estimation, with an average SOC error of less than 0.5%.

13. Thermal Imaging and Thermography

Wu et al. [124] presented an optimized LIB thermal fault diagnosis model using a modified mask region-based convolutional neural network (LBIP). The model accurately identifies and locates problematic batteries by processing thermal images of battery surfaces. LBIP-V2, the improved version, outperforms LBIP-V1 in most cases. Testing on various datasets demonstrates LBIP's recognition accuracy exceeding 95%. Additionally, real-time fault diagnosis simulations on 1P3S battery packs show LBIP's effectiveness in responding to online faults with over 98% confidence.

14. Model-Based Prognostics

Mishra et al. [125] aimed to diagnose Li-ion batteries using real-world NASA data and sensor fusion algorithms, primarily focusing on voltage and current measurements to assess battery health. Models were parameterized using recursive least squares filters, with batch-wise proving more reliable. These models, along with Kalman filters, tracked internal resistance increase and SOC. While successful in health tracking, Kalman filters could not refine SOC estimation, revealing a limitation. Nevertheless, the study demonstrated the viability of model-based approaches and sensor fusion algorithms for meaningful battery health tracking.

15. Frequency Response Analysis (FRA)

Fan et al. [126] presented a novel method utilizing experimental NFRA measurements to identify LIB aging history. A regression model trained on simulated NFRA data effectively quantifies degradation modes without prior knowledge of battery duty, highlighting the significance of multiple OCVs and frequencies for comprehensive characterization. The approach demonstrated promise for enhancing battery management strategies and second-life applications, with the potential for further improvement through robust regression analysis and expanded testing conditions.

Kim et al. [127] integrated time-domain and frequency-domain aging features for estimating the SOH of LIBs to comprehensively assess internal degradation. Extracting information such as the incremental capacity curve and electrochemical impedance spectroscopy, the approach addressed challenges like disappearing IC peaks and captured both time- and frequency-domain aging behaviors. Utilizing sparse spectrum Gaussian process regression, the model achieves low mean absolute error (MAE) and RMSE on NCA battery datasets across varying temperatures, demonstrating its effectiveness in SOH prediction.

16. Summary

The provided paper contains information related to the application of transformer-based models and BERT for LIB health prediction and state estimation, as well as various machine learning and AI techniques applied to battery management. Some of the key features of the LIB health study are described in Table 8. Different methods for health monitoring and state estimation in LIB are described in Table 9.

Table 8. Some of the key features of the LIB health study.

Key Features	Characteristics
Advances in Battery Technology	• Notable progress has been made in battery technology in the last decade, with a focus on LIBs. • Transformed the landscape of electric vehicle (EV) technologies. • Unlocked fresh opportunities for environmentally friendly and sustainable transportation.
Importance of State-of-Health (SOH) Estimation	• Precise assessment of the state-of-health (SOH) of LIBs is essential. • SOH serves as a comprehensive gauge of condition and performance, ensuring reliability, safety, and cost-effectiveness, particularly in EVs. • Its significance also encompasses broader applications in consumer electronics, preventing potential hazardous incidents.
Challenges in SOH Estimation	• Estimating the state-of-health (SOH) presents challenges, requiring time-consuming and labor-intensive procedures. • This task is particularly arduous in EVs due to restricted charge and discharge cycles, affecting the availability of historical data. • Conventional methods depend on analyzing features derived from measured signals under stringent operating conditions.
Forecasting RUL	• Precise prediction of RUL is crucial for prolonging battery lifespan and ensuring safety. • The challenge lies in accurate RUL forecasts when faced with limited charge and discharge cycles.
Natural Degradation of LIBs	• LIBs undergo natural degradation over time due to usage and environmental conditions. • This degradation has an impact on both energy storage and power delivery.
Challenges in Predicting Capacity and Power Fade	• Forecasting the capacity and power fade of LIB cells is challenging, given manufacturing variations and intricate nonlinear aging processes.
Interest in LIBs State Estimation for Researchers	• Researchers place significant emphasis on precise state estimation of LIBs. • The design of LIBs entails balancing considerations such as energy density, safety, and cost-effectiveness.
Role of Machine Learning (ML)	• Machine learning (ML) is increasingly recognized for addressing challenges in LIB state estimation. • ML techniques adeptly manage large datasets and intricate patterns, enhancing accuracy and efficiency. • This approach holds promising solutions for the future of battery technology.
Summary	
• Precise estimation of state-of-health (SOH) and RUL is crucial for diverse applications. • Challenges in this endeavor encompass constraints such as scarce historical data, intricate aging processes, and manufacturing variations. • The growing application of machine learning is contributing to improved accuracy and efficiency in LIB state estimation, presenting promising solutions for the future.	

Table 9. Different methods for health monitoring and state estimation in LIB.

Methods	Characteristics
Transformers for Time Series Analysis	• Convtrans showcases precise predictions for RUL, particularly in multi-step forecasting, and exhibits resilient generalization capabilities across diverse datasets.
Machine Learning-based Digital Twin	• Employing real-time modeling to capture battery behavior. • Leveraging historical data to construct SOH and SOC models with exceptional accuracy. • This framework is designed for real-time modeling of battery behavior, incorporating data-driven models trained on historical battery data, including accurate SOH and SOC models. It demonstrates high precision and suitability for onboard execution.
Unsupervised Learning	• Integrates EIS with Gaussian process machine learning to achieve precise forecasting of LIBs. • The combination of EIS and Gaussian process machine learning is employed for accurate forecasting of LIBs, providing reliable predictions of RUL and SOH based on a substantial dataset that includes EIS spectra for LIBs.
Meta-Learning	• Employs data from numerous batteries in pre-training, facilitating rapid adaptation. • Introduces a novel strategy for SOC estimation, leveraging pre-training with data from multiple batteries to achieve swift adaptation and high accuracy in SOC estimation.
Adversarial Training	• Applies adversarial training to enhance SOH estimation accuracy. • Implements adversarial training for SOH estimation, incorporating a feature alignment metric for domain-invariant features. This approach enhances feature learning, facilitates knowledge transfer, and ultimately improves the accuracy of SOH estimation.
Generalized SOH Model	• Suggests a regression GAN approach tailored for batteries with distinct specifications. • Introduces a regression GAN approach designed for batteries with specific specifications, aiming to develop a generalized model. This approach enhances the accuracy and robustness of SOH estimation.

Table 9. *Cont.*

Methods	Characteristics
Adversarial Learning for Lifespan Estimation	• Integrates adversarial learning and feature selection to estimate lifespan. • Combines adversarial learning and feature selection techniques for lifespan estimation, specifically addressing variations in degradation feature trajectories. This approach enhances deep learning-based battery health diagnostics.
GAN-CLS and BLSTM for State Prediction	• Combines GAN-conditional latent space (GAN-CLS) with BLSTM to decrease modeling time and boost prediction accuracy for LIBs.
Attention Mechanisms	• Introduces an innovative method for precise SOC estimation in LIBs by employing a dual-stage attention mechanism within an encoder–decoder network.
Continual Learning	• The utilization of online elastic weight consolidation is identified as a promising approach, with its effectiveness influenced by task characteristics and the sequence of tasks.
Graph Neural Networks	• Structures data into a graph-like format for the estimation of LIBs' capacity. • Integrates data from diverse sensors into a graph-like structure within a graph neural network, improving adaptability and performance in estimating LIBs' capacity, even in noisy environments.
Reinforcement Learning	• Takes into account a precise degradation model, demonstrating superior performance in energy arbitrage. • This approach considers both a detailed degradation model and uncertainties in the degradation patterns of LIBs, showcasing better performance in energy arbitrage compared to conventional methods.
Digital Twins for Electric Vehicle SoX Battery Modeling	• Achieves precise SOC capture in real-time through data-driven models. • A digital twin framework effectively captures the SoC during runtime operations by employing data-driven models trained with historical battery performance data.
Brain-Inspired Spiking Network Framework	• Integrates spiking neural networks (SNN) with self-attention modules for effective battery monitoring. • Combines spiking neural networks (SNN) with self-attention mechanisms to achieve efficient battery monitoring, accurately identifying battery degradation trends with minimal energy consumption.
Energy-Based Models	• Applies Gaussian process regression for enhanced SOH estimation. • Utilizes Gaussian process regression (GPR) along with improved modeling to enhance the effectiveness and precision of SOH estimation.

17. Current Problems and Challenges

1. Data Distribution Discrepancies: Existing methods often assume consistent data distribution for training and testing, leading to inefficiencies when applied to datasets under different working conditions [123].
2. Limited Historical Data: Accurate estimation of the state-of-health (SOH) and RUL of LIBs is hindered by limited historical data availability, especially considering the complex aging processes and manufacturing variations [124].
3. Complexity of Multiphysics and Multiscale Systems: Modeling and forecasting multi-physics and multiscale electrochemical systems, particularly under realistic conditions, pose formidable challenges due to their inherent complexity [125].
4. Interpretability of Deep Learning Models: Deep learning methodologies, while showing promise in simulating LIBs, often lack interpretability, making it difficult to understand model decisions and results [126].
5. Adaptability to Operational Changes: Current data-driven fault prediction approaches struggle to adapt flexibly to changes in operational or environmental parameters, hindering their effectiveness in real-world scenarios [127].

18. Future Development Directions and Prospects

1. Enhanced Training Processes: Transfer learning emerges as a valuable tool to enhance the training process of digital battery twins, offering increased data and computational efficiency [128].
2. Advanced AI Techniques: Transformer-based models and bidirectional encoder representations from transformers (BERT) show promise in enhancing LIB health prediction. Coupled with preprocessing methods and innovative equalizers, they offer significant improvements in RUL, SOH, and SOC estimation [129].
3. Cloud-Edge Computing: Utilizing cloud-edge computing, along with self-supervised transformer neural networks, holds potential for addressing the complexities of

multiphysics and multiscale systems, thereby enhancing battery management and performance forecasting [130].

4. Continued Research and Development: Continued efforts in research and development are essential to overcome current challenges and fully realize the potential of AI in revolutionizing battery technology. This includes addressing data distribution discrepancies, improving adaptability to operational changes, and enhancing the interpretability of deep learning models [131].

19. Conclusions

The review analyzes successful examples of AI implementation, discusses challenges faced in deploying AI in real-world scenarios, and proposes an integrated framework.

State-of-the-art research on machine learning (ML) applications in property prediction and battery discovery, encompassing electrolyte and electrode materials, is summarized. Additionally, the prediction of battery states is discussed.

This exploration delves into the transformative impact of advanced techniques, particularly transformer-based models and bidirectional encoder representations from transformers (BERT), on predicting the health of LIBs. The integration of preprocessing techniques, such as DAE and EIS data analysis, along with innovations like self-supervised transformer neural networks, proves effective in addressing challenges related to RUL, SOH, and SOC prediction. The study underscores the applicability of these advancements in practical domains such as EVs and energy storage systems. Despite the promises, challenges persist, including the need for continual learning to enhance fault prediction and addressing distribution discrepancies in training and testing data, ultimately aiming to improve the accuracy of predictive models.

Accurate estimation of the state-of-health (SOH) and RUL of LIBs is critical for the reliability, safety, and cost-effectiveness of various applications, including EVs and consumer electronics. This is a challenging task due to factors such as limited historical data, complex aging processes, and manufacturing variations. To overcome these challenges, machine learning techniques have been increasingly applied to improve accuracy and efficiency in LIB state estimation, offering promising solutions for the future of battery technology.

In summary, this comprehensive review has systematically examined successful instances of AI implementation, delved into challenges encountered in real-world AI deployment, and proposed an integrated framework. The survey of state-of-the-art research in machine learning applications, specifically in property prediction and battery discovery, highlighted the critical aspects of electrolyte and electrode materials. Furthermore, the paper extensively covered battery state prediction, emphasizing the importance of accurately estimating state-of-charge (SOC) for safe and efficient electric vehicle (EV) operation.

Addressing the challenges in modeling and forecasting multiphysics and multiscale electrochemical systems, particularly under realistic conditions, has proven to be a formidable task. While deep learning, particularly through CNNs and recurrent neural networks (RNNs), has gained popularity for state-of-health (SOH) estimation, the full potential of these methods remains underutilized.

Transfer learning emerges as a valuable tool to enhance the training process of digital battery twins, offering increased data and computational efficiency. Despite its success in achieving a mean SOH deviation of 0.05%, the need for including pauses in the dataset for accurate SOH estimation is underscored.

The application of deep learning in LIB online health diagnostics, using cloud and edge computing with big data, has seen widespread adoption. However, challenges persist in improving the accuracy, robustness, and real-time applicability of these diagnostics. Notably, the oversight in degradation feature trajectories between training and testing domains affects the precision of the trained model's estimation.

CNNs have demonstrated promise in online LIBs capacity estimation, but the requirement for significant aging data poses challenges. Efficient data collection in real-world applications, coupled with the demand for extensive memory storage due to numerous parameters, remains a practical concern.

Accurate SOH estimation of LiBs using data-driven methods faces challenges due to operational constraints and sensor failures. The utilization of regression GANs emerges as a potential solution to develop a general model for batteries with precise specifications.

Temperature monitoring in LiBs is crucial for performance improvement and risk mitigation. Leveraging convolutional transformers (Convtrans) for multi-step time series forecasting shows promise in addressing the temporal aspect of LIBs temperature.

Despite the success of artificial neural networks (ANNs) in the domain, their limitations in energy consumption and generalization prompt exploration of brain-inspired spiking neural networks (SNNs) as an alternative approach.

Ensuring the safety and reliability of LiBs requires accurate prediction of SOH and RUL. Existing prediction methods often fall short of revealing feature correlations, hindering optimal results. Establishing these correlations can enhance the predictive model's accuracy.

The paper underscores the challenges of existing methods, which assume consistent data distribution for training and testing. This assumption proves ineffective when applied to datasets under different working conditions due to distribution discrepancies.

Estimating LIBs capacity is vital for health management, with traditional methods relying on time-consuming handcrafted feature engineering. Data-driven methods, while effective, pose practical challenges in real-world applications.

Early prediction and understanding of LIBs faults are crucial for product quality. Current data-driven fault prediction approaches provide good results but struggle to adapt flexibly to changes in operational or environmental parameters. Continual learning offers the promise of automatic adaptation to new tasks.

In conclusion, the paper positions transformer-based models and bidirectional encoder representations from transformers (BERT) as powerful tools for enhancing the prediction of LIB health and state estimation. The integration of these advanced techniques with preprocessing methods and innovative equalizers demonstrates significant improvements in RUL, SOH, and SOC estimation. Cloud-edge computing, coupled with self-supervised transformer neural networks, holds promise for addressing the complexities of multiphysics and multiscale systems, enhancing battery management, and performing performance forecasting. The collective findings emphasize the substantial impact of advanced techniques on LIB health prediction, positioning them as promising candidates for practical applications in EVs and energy storage systems.

The review also highlights the attention garnered by deep learning approaches in simulating LIBs, attributed to their ability to understand intricate relationships within battery systems and improve predictive accuracy. Challenges in this field include the need for large and diverse datasets, the interpretability of deep learning models, and ensuring model transferability across various battery chemistries and operating conditions. While deep learning methodologies show potential, integration with physics-based models is crucial, leading to the exploration of hybrid models as an actively researched area.

In conclusion, this paper has provided a thorough analysis of successful AI implementations, discussed the challenges encountered in real-world deployment, and proposed an integrated framework for addressing these challenges. The review of state-of-the-art research in machine learning applications, particularly in property prediction and battery discovery, has shed light on critical aspects such as electrolyte and electrode materials, as well as battery state prediction, emphasizing the importance of accurately estimating state-of-charge (SOC) for safe and efficient electric vehicle (EV) operation.

However, challenges persist in modeling and forecasting multiphysics and multiscale electrochemical systems, especially under realistic conditions. While deep learning methods like CNNs and recurrent neural networks (RNNs) have gained popularity for state-of-health (SOH) estimation, their full potential remains underutilized. Transfer learning offers a promising approach to enhancing the training process of digital battery twins, although challenges such as the need for including pauses in datasets for accurate SOH estimation are underscored.

The application of deep learning in LIB online health diagnostics, utilizing cloud and edge computing with big data, has shown widespread adoption but faces challenges in improving accuracy, robustness, and real-time applicability. CNNs hold promise in online LIBs capacity estimation, but efficient data collection and storage present practical concerns. Additionally, ensuring the safety and reliability of LiBs requires accurate prediction of SOH and RUL, which current methods often struggle to achieve due to assumptions of consistent data distribution.

Furthermore, while artificial neural networks (ANNs) have shown success in the domain, their limitations in energy consumption and generalization prompt exploration of brain-inspired spiking neural networks (SNNs) as an alternative approach. However, challenges remain in establishing feature correlations for optimal predictive model accuracy and adapting flexibly to changes in operational or environmental parameters.

In light of these challenges, transformer-based models and bidirectional encoder representations from transformers (BERT) emerge as powerful tools for enhancing LIB health prediction. Integration with preprocessing methods and innovative equalizers has shown significant improvements in RUL, SOH, and SOC estimation. Cloud-edge computing, coupled with self-supervised transformer neural networks, holds promise in addressing the complexities of multiphysics and multiscale systems, thereby enhancing battery management and performance forecasting.

In summary, this review underscores the substantial impact of advanced techniques on LIB health prediction, positioning them as promising candidates for practical applications in EVs and energy storage systems. However, continued research and development are essential to overcome current challenges and fully realize the potential of AI in revolutionizing battery technology.

Despite the promising advancements in AI implementation for LIBs, several challenges hinder their widespread adoption and optimal performance in real-world scenarios. One critical issue lies in the assumption of consistent data distribution for training and testing, which proves ineffective when applied to datasets under different working conditions. Moreover, the limited availability of historical data poses challenges in accurately estimating the state-of-health (SOH) and RUL of LiBs, especially considering the complex aging processes and manufacturing variations inherent in these systems.

Additionally, the complexity of multiphysics and multiscale electrochemical systems presents formidable challenges in modeling and forecasting, particularly under realistic conditions. Furthermore, while deep learning methodologies show promise in simulating LiBs, their lack of interpretability complicates understanding model decisions and results. Furthermore, current data-driven fault prediction approaches struggle to adapt flexibly to changes in operational or environmental parameters, hindering their effectiveness in real-world scenarios.

However, there are promising avenues for future development in addressing these challenges. Integrating deep learning methods with physics-based models offers the potential to enhance predictive accuracy and interpretability through hybrid models. Transfer learning presents an opportunity to enhance the training process of digital battery twins, improving data and computational efficiency. Advanced AI techniques such as transformer-based models and bidirectional encoder representations from transformers (BERT) hold promise in enhancing LIB health prediction, offering significant improvements in RUL, SOH, and SOC estimation when coupled with preprocessing methods and innovative equalizers.

Furthermore, leveraging cloud-edge computing and self-supervised transformer neural networks could address the complexities of multiphysics and multiscale systems, thereby enhancing battery management and performance forecasting. Continued research and development efforts are crucial to overcoming current challenges, including addressing data distribution discrepancies, improving adaptability to operational changes, and enhancing the interpretability of deep learning models. These endeavors are essential to fully realizing the potential of AI in revolutionizing battery technology and enabling its practical applications in EVs and energy storage systems.

The literature review presents a diverse array of methodologies aimed at estimating the health state and SOH of LIBs. Techniques such as EIS are leveraged alongside data-driven approaches like neural networks to efficiently estimate LIBs' health states, highlighting the importance of selecting appropriate health indicators. Voltage and current profiling methods explore constant-current (CC) and constant-voltage (CV) charging curves, demonstrating promising results in SOH estimation and suggesting different charging profiles offer valuable insights into battery health. Coulomb counting approaches focus on precise state-of-charge (SOC) estimation, with modified methods and fault diagnosis algorithms contributing to improved accuracy and real-time monitoring, crucial for electric vehicle applications.

Furthermore, model-based prognostics and frequency response analysis (FRA) offer sophisticated means of tracking battery health. Model-based approaches utilize real-world data and sensor fusion algorithms for health tracking, while FRA techniques provide insights into battery aging history and SOH estimation through comprehensive characterization and integration of time and frequency domain features. Additionally, thermal imaging and thermography methods present innovative ways of diagnosing battery faults based on thermal images, showcasing high recognition accuracy and responsiveness to online faults. Integrating these diverse methodologies and considering different battery characteristics could lead to a more accurate and comprehensive battery health assessment, which is essential for ensuring optimal performance and longevity in various applications.

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