Energy and AI 18 (2024) 100419

Contents lists available at ScienceDirect

Energy and AI

journal homepage: www.sciencedirect.com/journal/energy-and-ai

Artificial intelligence-driven real-world battery diagnostics

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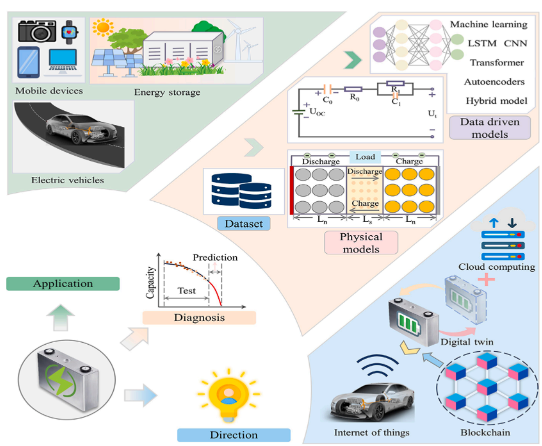
HIGHLIGHTS

- Highlights specialized deep learning approaches for predicting real-world battery health.
- Explores deep learning to address challenges in battery diagnostics under field conditions.
- Examines limitations such as computational costs, explainability, and the application gap.
- Anticipates the roles of AIOps, lifelong machine learning, and cloud digital twin technologies.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Battery
Safety
Health
Lifetime
Artificial intelligence
Machine learning
Electric vehicle
Deep learning

ABSTRACT

Addressing real-world challenges in battery diagnostics, particularly under incomplete or inconsistent boundary conditions, has proven difficult with traditional methodologies such as first-principles and atomistic calculations. Despite advances in data assimilation techniques, the overwhelming volume and diversity of data, coupled with the lack of universally accepted models, underscore the limitations of these traditional approaches. Recently, deep learning has emerged as a highly effective tool in overcoming persistent issues in battery diagnostics by adeptly managing expansive design spaces and discerning intricate, multidimensional correlations. This approach resolves challenges previously deemed insurmountable, especially with lost, irregular, or noisy data through the design of specialized network architectures that adhere to physical invariants. However, gaps remain

Abbreviations: AI, Artificial intelligence; AIOps, Artificial intelligence for IT operations; ASICs, Application-specific integrated circuits; BERTtery, Bidirectional encoder representations from transformers for batteries; BMS, Battery management system; CNNs, Convolutional neural networks; EVs, Electric vehicles; FPGAs, Field-programmable gate arrays; GPU, Graphics processing unit; GRU, Gated recurrent units; IoT, Internet of things; LFP, Lithium iron phosphate; LSTM, Long short-term memory networks; MAE, Mean absolute error; MAPE, Mean absolute percentage error; NCA, Nickel cobalt aluminum; RMSE, Root mean square error; SOC, State of charge; SOH, State of health; TPU, Tensor processing unit; XAI, Explainable artificial intelligence; XGboost, eXtreme gradient boosting.

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https://doi.org/10.1016/j.egyai.2024.100419

Available online 29 August 2024

Real world
Field

between academic advancements and their practical applications, including challenges in explainability and the computational costs associated with AI-driven solutions. Emerging technologies such as explainable artificial intelligence (XAI), AI for IT operations (AIOps), lifelong machine learning to mitigate catastrophic forgetting, and cloud-based digital twins open new opportunities for intelligent battery life-cycle assessment. In this perspective, we outline these challenges and opportunities, emphasizing the potential of innovative technologies to transform battery diagnostics, as demonstrated by our recent practice and the progress made in the field. This includes promising achievements in both academic and industry field demonstrations in modeling and forecasting the dynamics of multiphysics and multiscale battery systems. These systems feature inhomogeneous cascades of scales, informed by our physical, electrochemical, observational, empirical, and/or mathematical understanding of the battery system. Through data assimilation efforts, meticulous craftsmanship, and elaborate implementations—and by considering the wealth and spatio-temporal heterogeneity of available data—such AI-based intelligent learning philosophies have great potential to achieve better accuracy, faster training, and improved generalization.

1. Background

The reduction of carbon emissions in transportation is closely linked to the rise of electric vehicles (EVs) powered by lithium-ion batteries [1,2],. Lithium-ion batteries play a crucial role in EVs, as their performance directly influences the user experience and the rate of EV adoption [3,4], . In the coming decades, battery costs are expected to decrease further due to technological advancements, economies of scale, and mass adoption, particularly in electrified transportation applications [5,6],. Studies indicate that rechargeable batteries have significant potential to dominate the zero-emission vehicle (ZEV) markets, including both light-duty vehicles (LDVs) [7] and medium- and heavy-duty vehicles (MHDVs) [8]. However, several challenges hinder the widespread adoption of EVs, including limited driving range, battery degradation, and safety concerns. In this context, accurately diagnosing and predicting battery health can offer vital insights into safety and assist in forecasting lifespan and failure risks [9-14]. Despite extensive research on battery behavior and aging [15,16], real-world applications of predictive capabilities still encounter specific limitations [17].

In recent years, the diagnostics field has undergone a transformative phase, driven by advancements in computational capabilities and the integration of data-driven, open-source technologies [18-20]. Traditional model-based approaches often struggle to address the challenges posed by the complexity and unpredictability of scenarios encountered in the battery domain [21-24]. The gap between controlled academic experiments and real-world conditions, in particular, poses significant obstacles. In this context, the emergence of machine learning marks a substantial paradigm shift [25-27]. Machine learning techniques excel at identifying patterns in complex, high-dimensional data, thereby opening new avenues for research and application in the battery domain [28,29],. Furthermore, given its capacity to process vast datasets [30], machine learning has demonstrated its efficacy as a powerful instrument within the battery industry, enabling a seamless transition from theoretical research to practical implementations. The application of machine learning models in the field of battery diagnostics necessitates high standards for input data quality. Challenges such as data incompleteness, irregularity, and noise make the implementation of refined data preprocessing and deep learning techniques particularly crucial. Specifically, techniques such as data interpolation and resampling are widely employed to complete missing data points and create regular time intervals, laying a comprehensive data foundation for subsequent deep learning analysis. During the feature extraction phase, the use of convolutional neural networks (CNNs) proves essential, as they can autonomously identify and extract useful features from raw data. These features demonstrate strong resistance to irregularities and noise in the data, thereby enhancing the overall robustness of the model. Through their complex multi-layer structures, CNNs effectively capture local characteristics within the data, thus providing solid support for accurate diagnostics of battery states. Moreover, for time series data, long short-term memory networks (LSTM) and gated recurrent units (GRU) exhibit remarkable performance. These models, through their unique designs, adeptly handle long-term dependencies in the data, enabling accurate predictions even in cases of significant data gaps or noise. LSTMs and GRUs utilize internal gating mechanisms to regulate the flow of information, thereby mitigating common issues of gradient vanishing or exploding in long-term dependency analyses. This mechanism ensures that the models maintain high performance even when faced with incomplete sequence data.

Driven by advances in intelligence and data-driven technologies, the electric vehicle industry is increasingly adopting artificial intelligence (AI) to optimize battery management systems and enhance energy efficiency. A recent groundbreaking study proposed a data-driven diagnostic framework designed to effectively detect anomalies in battery charging capacity by analyzing extensive data from electric vehicle operations [31]. Specifically, the study utilized four key parameters as input variables: state of charge changes (SOC change), ambient temperature, cumulative mileage, and the time required to increase one SOC unit. By employing the XGBoost regression model, the framework was capable of handling charging process data across different charging rates and optimizing results through a refined classification process. The research team accessed a rich data resource from the China national new energy vehicle monitoring and management center and the national data alliance of new energy vehicles open lab, including detailed information on vehicle speed, cumulative mileage, battery voltage, and current. Comparative analysis with seven existing prediction models, including linear regression, proportional models, Lasso regression, neural network models, random forest regression, support vector regression, and AdaBoost models, was conducted. Results indicated that the data-driven framework exhibited superior predictive accuracy with a mean absolute error (MAE) of 1.23, outperforming other models. Another study introduced a novel state of health (SOH) estimation model based on Catboost and intermediate capacity during the charging process [32]. This model relied on data collected over a year from a big data platform specifically monitoring public service vehicles, including real-time data from 15 variables such as battery systems, driving behaviors, and environmental factors. Using incremental capacity analysis to extract aging characteristics from charging data and employing the K-means++ algorithm to classify charging segments based on charging currents, the model achieved a mean absolute percentage error (MAPE) of 2.74 % and a root mean square error (RMSE) of 1.12 %, surpassing common machine learning methods in SOH estimation. Recent research introduced a method for predicting battery capacity that utilizes charging data combined with data-driven algorithms [33]. A sequence-to-sequence model, utilizing LSTM networks, forecasts future battery capacities. This model integrates a residual framework employing Gaussian process regression to offset errors induced by temporal and thermal variations. After validation with data spanning 29 months from 20 electric vehicles, it was found that initial three-month data could precisely forecast the battery capacity for the following 23 months, achieving an MAE of 1.24 % and an RMSE of 1.53 %. Compared to support vector regression and iterative prediction methods, this model exhibited superior predictive accuracy. These studies highlight the substantial benefits of AI in improving both the accuracy and efficiency of electric vehicle battery diagnostics, while also demonstrating practical applications of these technologies. By optimizing battery performance management, the application of these technologies contributes to the sustainable development of electric vehicles, extends battery life, reduces maintenance costs, and improves overall operational efficiency.

Our previous research has pursued two significant directions to enhance the predictive performance and diagnostic capabilities of battery systems. Initially, we developed an innovative technique utilizing a specialized Transformer architecture, which we have named BERTtery [34]. BERTtery is a dual-tower Transformer network model specifically designed to parse spatiotemporal data collected during battery operation. This model extracts complex patterns and dependencies within the data, enabling precise predictions of potential failures and malfunctions in battery systems. Specifically, the BERTtery model initially undergoes pre-training on a large, unlabeled dataset to learn fundamental feature representations of various failure and malfunction scenarios. This step provides the model with deep data understanding and pattern recognition capabilities. Following pre-training, the model is fine-tuned with task-specific data to optimize its performance in specific fault diagnosis tasks. Additionally, the model employs sine and cosine functions to encode positional information, a unique encoding method that effectively maps the positional relationships of battery charging and discharging curves within time series data. This positional encoding, combined with the self-attention mechanism of the model, significantly enhances its ability to process complex, multidimensional spatiotemporal data. Through the self-attention mechanism, BERTtery focuses on analyzing the most critical features within the data, thus providing accurate predictions of faults and failures. The innovativeness of the BERTtery model is primarily reflected in its structure designed specifically for battery data, its deep pre-training strategy, and advanced encoding techniques. These features exhibit excellent predictive performance, introducing new ideas and solutions to the field of battery fault diagnosis. In another direction, our previous study employed a stacked ensemble machine learning approach [35]. We utilized real operational data from nine EVs to validate a SOH prediction model. During validation, our model demonstrated remarkable precision, with a MAPE of 0.28 % and a artifitierror of 0.55 % in capacity estimation. These data underscore the high reliability of machine learning methods in real-world battery systems, providing robust support for improvements in reliability and performance in the EV industry. Collectively, these studies illustrate the substantial potential of machine learning technology in onsite battery diagnostics, providing valuable insights and guidance for the continued development of EVs and energy storage systems. However, despite the significant progress made by machine

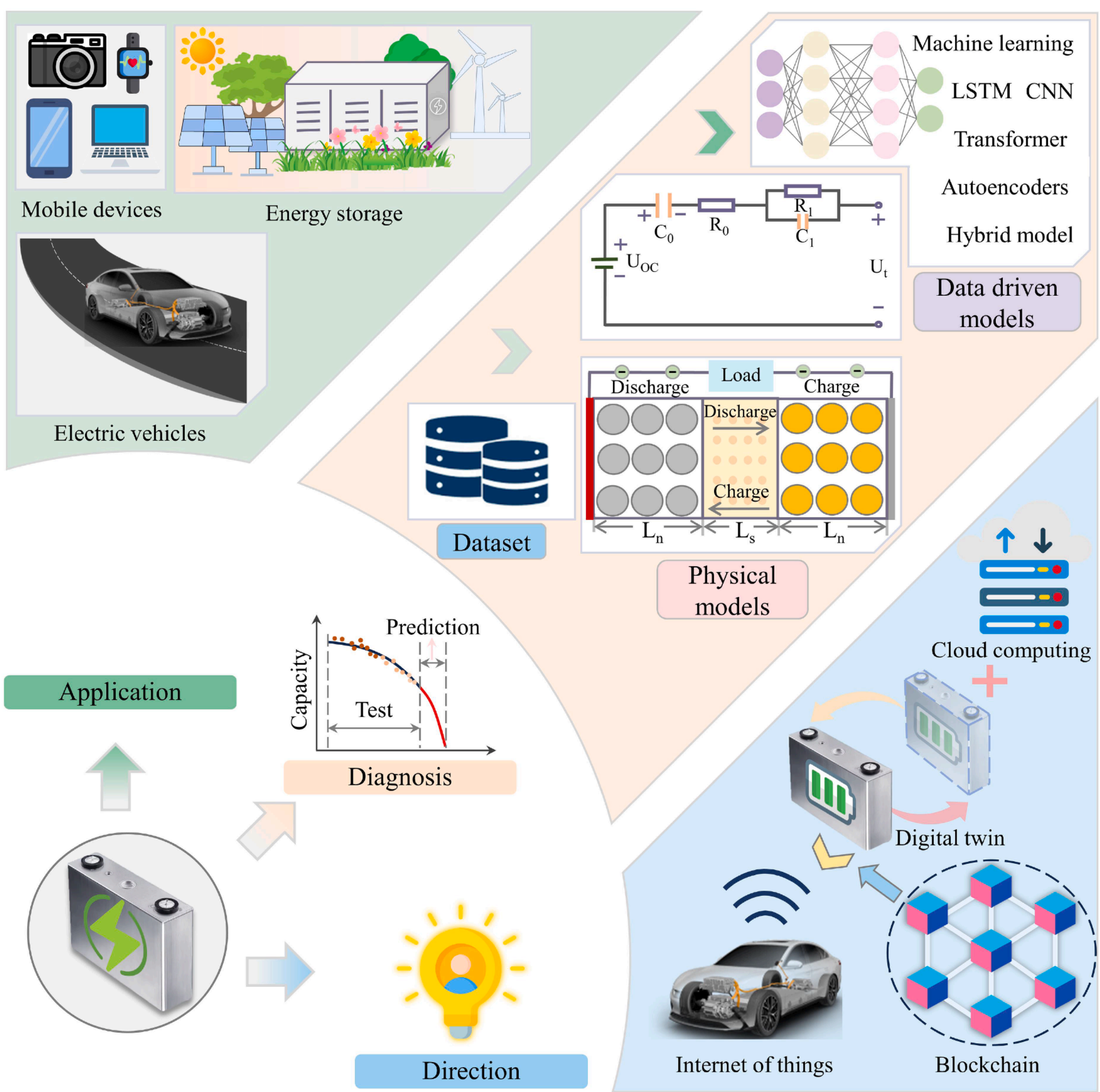

Fig. 1. The integration and innovation of battery diagnostic techniques in practical applications.

learning techniques in the field of batteries, there are still numerous challenges to be addressed [36]. For instance, further research and enhancement are necessary in areas such as data quality and reliability, algorithm interpretability, and the scalability and robustness of applications.

In the framework of Industry 4.0, the field of battery diagnostics has incorporated several key technologies, including digital twins [37], edge computing [38], cloud computing [39,40], and blockchain [41] (Fig. 1). Digital twin technology, which creates virtual replicas of battery systems, enables precise simulations of actual battery performance and behavior under various operational conditions [42-44]. Researchers use digital twins to conduct extensive experiments in a virtual setting, thereby accelerating the development and validation of diagnostic and predictive models. To accurately estimate the SOH of lithium-ion batteries in real-time under dynamic conditions, a study incorporated digital twin technology [45]. Utilizing a digital twin framework combined with partial discharge data, the research real-time evaluated battery SOH. In addressing the varied training cycle data, the study introduced an energy difference-aware dynamic time warping method (EDTW), which ensured data structure consistency by aligning cycle data. This model, through data encoding techniques, effectively captured the degradation behavior of batteries during usage, eliminating the negative impact of non-critical samples and accurately assessing the influence of different training sampling times. Additionally, the study introduced a data reconstruction method based on similarity analysis, enabling real-time SOH estimation without complete discharge cycles. With an online data reconstruction strategy, real-time SOH estimation was achievable using only partial discharge data, maintaining an estimation error within 1 %. Further research employed a digital twin technology-based framework focused on real-time prediction of lithium-ion battery degradation performance [46]. This framework integrated CNN, LSTM, and attention mechanisms to enhance the accuracy of real-time predictions of maximum available capacity for the battery. By employing a back propagation neural network to supplement partial discharge voltage curves, the study obtained more comprehensive discharge voltage information. Using a CNN-LSTM-Attention model, critical features were extracted from current discharge voltage curves to construct an accurate battery capacity prediction model, facilitating real-time feedback on battery degradation performance. The reliability of this method was validated through a publicly available battery dataset from Oxford University, with experimental results showing that the digital twin system could precisely supplement partial discharge voltage curves and accurately predict maximum available capacity for the battery, maintaining a prediction error below 3 mAh under various cycle conditions. Traditional cloud computing models often encounter challenges such as data transmission delays and network congestion. Edge computing addresses these issues by shifting computational capabilities for data processing and analysis closer to the data sources [47], enabling more immediate and real-time diagnostics and predictions. In a related study, a cloud-edge based management system for electric vehicle batteries was proposed, leveraging cloud computing and edge computing technologies to enhance the accuracy of battery state estimation [48]. By integrating cloud computing resources and big data resources, a cloud data mining and battery modeling method based on deep learning algorithms was developed to estimate battery voltage and energy states. At the vehicular system level, edge nodes within the battery management system were responsible for real-time collection of data from distributed sensors, actuators, and sub-controllers. This data was transmitted in real-time to the onboard BMS of the vehicle through a bidirectional data communication system., ensuring the timeliness and accuracy of battery state estimation. Concurrently, relevant battery operational data were uploaded to the cloud platform for further data mining and analysis. On the cloud platform level, the system utilized deep learning algorithms to mine extensive data from electric vehicle batteries deeply, constructing precise models for estimating terminal voltage and SOC. This model could predict the current state of the battery based on real-time and historical data, optimizing battery performance and lifespan management. Ultimately, bidirectional parameter transmission between vehicles and the cloud platform was realized through the edge computing network, enhancing data processing speed and efficiency. Research results indicated that this edge computing-based battery management system effectively supported the practical application of big data-driven vehicle management technologies, improving the accuracy of battery state estimation and the overall operational efficiency of the system. In battery diagnostics, ensuring data privacy and integrity is crucial. Blockchain technology enhances security by using decentralized storage and immutable records, providing a robust foundation for diagnostic and predictive models [49]. A study introduced a blockchain-based interpretable framework for predicting the lifespan of electric vehicle batteries, ensuring data security and transparency [50]. The research implemented a smart contract, DataKeeper, to manage vehicle identity information and secure legitimate access to vehicle data within the system. The smart contract stores a unique identifier for the vehicle upon its initial login, after which the vehicle can upload raw data and download predictive data. Initially, the framework collects and pushes vehicle information through edge devices and interacts with the blockchain network. Subsequently, the legality of the connected vehicles is verified through the blockchain network, and data access control is executed via the smart contract DataKeeper, ensuring the integrity and authenticity of the data. Finally, the prediction server downloads and decrypts vehicle data, uses the BLP-Transformer algorithm for battery life prediction, and then encrypts and uploads the predictive data to the blockchain. Experimental simulations validated the effectiveness of the framework, demonstrating its advantages in security and predictive accuracy. Introducing digital twins, edge computing, and blockchain technology into the field of on-site battery diagnostics provides new perspectives and solutions for on-site battery diagnostics and prediction.

Machine learning, especially deep learning, has made significant advances in solving problems that have long challenged the AI community. It excels at identifying complex structures within high-dimensional data, making it applicable across a broad range of scientific and technological domains. This is particularly pivotal for intelligent diagnostic technologies in Industry 4.0. Specifically, machine learning techniques for battery performance estimation include: (1) supervised learning [51,52], which can be integrated with battery models and is well-suited for predicting behaviors and investigating underlying causes and mechanisms at the cell level; (2) unsupervised learning [53,54], which is advantageous for leveraging large datasets from battery modules or packs; (3) semi-supervised learning [55,56], which combines elements of the first two approaches to enhance learning accuracy; and (4) self-supervised learning [57,58], which provides powerful tools for feature extraction and anomaly detection without requiring labeled data. These emerging directions not only promise to refine existing models but also pave the way for revolutionary developments in battery technology diagnostics and optimization. Given recent advances, a number of nice reviews has enhanced our understanding of battery performance evaluation through the application of machine learning techniques. These methodologies offer detailed insights into battery diagnostics, including the SOC [59,60], SOH [61,62], and critical safety issues [13,63],. Therefore, we focus primarily on discussing the primary challenges associated with using AI and machine learning in this context, while also highlighting some promising directions that warrant further exploration.

2. Challenges

In battery diagnostic technology, physics-based modeling and data-driven methods represent two prevalent approaches. Physics-based diagnostic techniques in batteries involve developing physical and mathematical models that elucidate internal processes such as electrochemical reactions, ion transport, and heat conduction [64]. This approach necessitates extensive experimental data and computational resources to validate and refine the accuracy and reliability of the models. However, practical battery diagnostics encounter limitations, including onboard battery management systems (BMS) data storage, data processing, and computational capabilities, which often impede the advancement of physics-based methods. To surmount these challenges, researchers and engineers have shifted focus to the potent field of AI [65]. Although data-driven, machine learning-based research has shown remarkable capabilities in modeling and predicting the dynamics of multiphysics and multiscale battery systems [66-68], applying these methods to complex battery systems under real-world conditions is still challenging (Fig. 2).

(1). The gap between academia and real-world

Battery diagnostics are essential for advancing EVs and renewable energy storage systems. However, bridging the gap between academic research and field applications necessitates addressing several challenges. These challenges include the complexity and variability of real-world environments, limitations in data acquisition and experimental conditions, model reliability and applicability, and the necessity for real-time, practical solutions [69,70],.

Battery safety and health are critical for their reliable operation in specific applications. In laboratories, scientists study battery behavior under controlled conditions to simulate performance and degradation processes. These conditions are precisely controlled, with variables such as temperature, voltage, and current meticulously regulated. However, in real-world applications, batteries face much more complex and variable environments, including temperature fluctuations, inconsistent charging methods, and diverse load conditions. The ultimate goal of diagnostics is to predict future performance, but due to the variability of real-world operations, laboratory models often fail to effectively perform this predictive function [71]. Additionally, compared to standardized and high-precision data collection in academic laboratories [72], data acquisition in field applications encounters more challenges [17], such as limitations of high-precision sensor equipment, time costs, and privacy considerations. Consequently, the quality of field data and the accuracy of diagnostic models are often compromised by noise, interference, or incomplete data. This impact can result in diagnostic methods that perform well in small-scale laboratory tests failing to function effectively when scaled up to full-size field battery systems.

Enhancing the reliability and applicability of AI-based battery diagnostic models remains a pivotal challenge in the field. Recent studies have increasingly utilized machine learning and deep learning models to develop battery diagnostic systems [73-76]. However, these models are typically validated and optimized under controlled conditions and specific datasets. Long-term monitoring and data analysis are crucial for comprehensively understanding battery degradation processes. Laboratory research is constrained by the scarcity of diverse and comprehensive field battery data, which limits the adequate validation of diagnostic models for real-world reliability and applicability. As battery technology advances, the complexities of battery cycling and aging behavior have attracted increased attention, complicating battery diagnostics further [77]. In the face of continual advances in battery chemistry and design, diagnostic tools must be continually developed and validated to adapt to new battery types. These tools must be both technically advanced and user-friendly, enabling users to understand the data and make informed decisions with minimal training. Furthermore, diagnostic tools must support real-time or near-real-time monitoring and prediction of battery health, offering timely feedback and recommendations to ensure battery system safety and reliability. This situation presents new challenges in predictive diagnostics, from laboratory to field applications, necessitating more integrated approaches to tackle these issues.

Advancing battery diagnostic technology necessitates a comprehensive consideration of multiple factors. In addition to technical

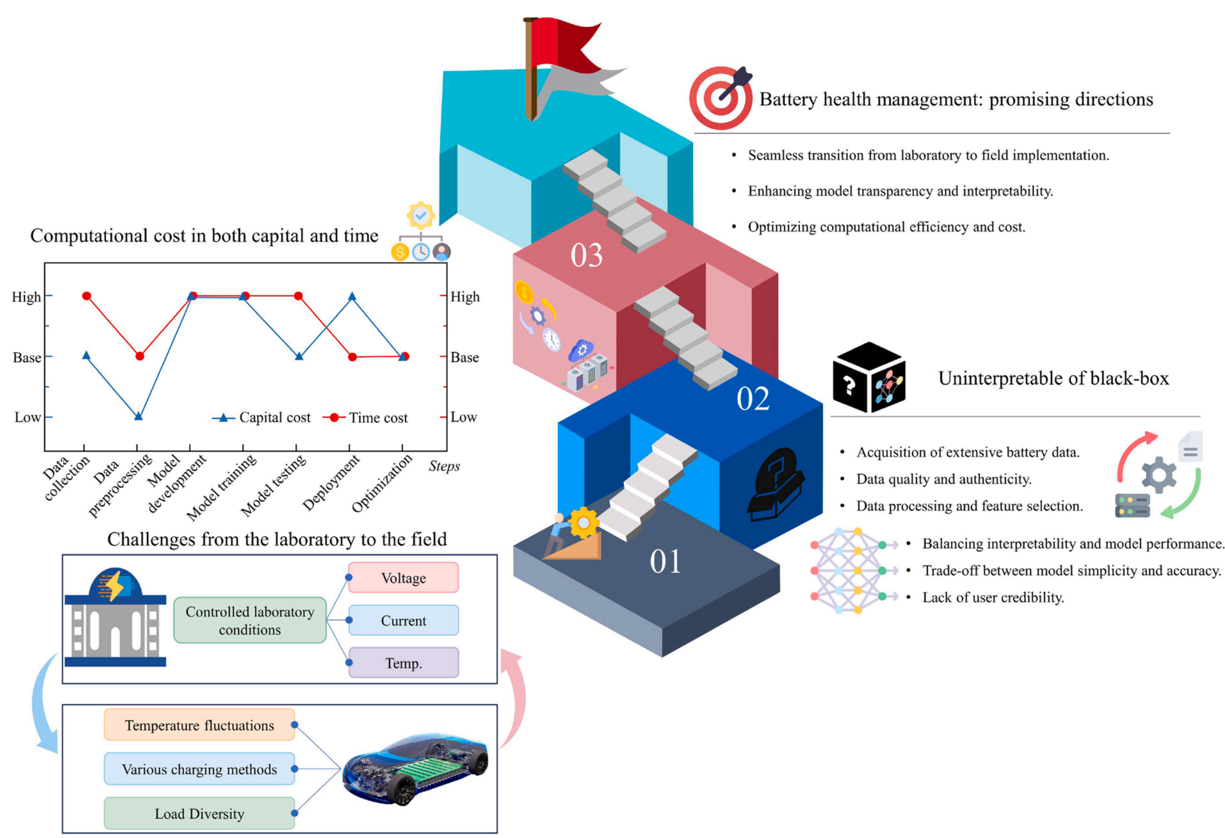

Fig. 2. Challenges faced by battery diagnostic methods under field conditions.

innovations, such as new diagnostic algorithms, sensor technologies, and data processing methods, consideration of the economic, practical, and regulatory aspects of battery usage is essential [78]. These include battery cost, energy efficiency, and sustainability. Therefore, ensuring a seamless transition from laboratory research to real-world applications, actively integrating laboratory findings with field applications, and effectively managing and analyzing field data are crucial for advancing battery technology.

(2). Explainable AI

The application of machine learning, especially deep learning and neural networks, has significantly enhanced battery diagnostics [61-80]. These models are trained using extensive battery data—including voltage, current, and temperature—and features pertinent to battery life and health, enabling the development of predictive models suited to various operational conditions and battery types [81]. Owing to the often-opaque nature of their decision-making processes, these models lack physical interpretability and are commonly referred to as "black boxes" [82]. This lack of transparency complicates efforts to trace how specific input features influence prediction outcomes.

The robust predictive capabilities of machine learning are increasingly evident in the field of high-risk decision-making and forecasting. To enhance trust in critical predictive tasks, the interpretability of these "black box" models is essential. Researchers have developed the field of explainable artificial intelligence (XAI) to clarify the opaque decision-making processes of machine learning algorithms [83,84],. Interpretability is categorized into intrinsic and post-hoc models [85-88]. Intrinsic models directly explain predictions through the architecture of the model [89], illustrated by decision tree models that classify or regress input data through simple, rule-based methods. For instance, in battery diagnostics, decision trees can analyze the relationship between battery characteristics and their health status, providing clear insights into the overall logic or specific predictions of the model. On the other hand, post-hoc interpretability models, decode the operations of existing models [90]. Local interpretability, a method aimed at explaining model behavior near specific data points, utilizes techniques such as local linear fitting to approximate a linear model at these points, thereby elucidating the prediction logic and feature importance at these locations [91]. Another post-hoc interpretability approach involves structural analysis, examining the architecture and parameters of the model. This may involve analyzing the weights of hidden layers in deep learning models to understand how predictions are made based on input features, revealing the decision logic and inherent rules of the model [92].

Although interpretable models elucidate the intricate interactions among factors influencing battery health, which is crucial for understanding predictive outcomes and supporting decision-making, creating models that are both accurate and interpretable presents several challenges [93,94],. These challenges include balancing simplicity with accuracy and the interdisciplinary expertise required for their development. In practical applications, enhancing interpretability often results in some degree of performance loss. For instance, simplifying model structures or limiting the use of features can reduce the predictive performance of models. The development of interpretable machine learning holds promise for battery diagnostics, suggesting that complex models will provide clear and actionable insights in the future. However, the pursuit of developing interpretable, accurate, and user-friendly methods remains a significant and ongoing area of research. Balancing interpretability and performance presents an additional challenge in implementing field diagnostics.

(3). Computational cost in both capital and time

Machine learning is increasingly becoming the most efficient tool for battery diagnostics, enabling precise predictions of battery health and lifespan through the analysis of extensive data sets. However, the application of machine learning in battery diagnostics presents considerable challenges in computational costs, both in capital and time resources [95]. The requirements for high-performance computing resources, the operation of complex algorithms, and the comprehensive processes of data preparation and model training pose substantial demands on resource allocation. Deep learning models, which are central to modern diagnostics, rely on processing vast data volumes and executing complex algorithms. These models require the management of extensive sensor data and execution of computationally demanding operations, making high-end computing hardware such as graphics processing units (GPUs), tensor processing units (TPUs), and large-scale parallel processing clusters essential [96,97],. The parallel computing capabilities of GPUs and TPUs significantly enhance the training and inference speeds of deep learning models [98,99],. However, acquiring and maintaining these advanced hardware components entails substantial costs, often necessitating significant capital investment. Additionally, the performance of data collection and storage devices must also be high to guarantee the reliability of real-time data processing and storage. Not only do these hardware devices require substantial initial investments, but they also demand the expertise of technical personnel for routine maintenance and management, further increasing the financial burden.

Whether in laboratory settings or in the field, utilizing AI methods for battery diagnostics presents substantial temporal challenges. In laboratory environments, collecting battery aging data often involves prolonged experiments. To ensure the generalizability of the model and generate diverse battery data, laboratories must test multiple battery types and models. This setting enables researchers to conduct repeated experiments to identify and validate the most valuable features, ensuring through iterative refinement that the model captures critical indicators of battery performance. Moreover, model training and validation represent the most time-consuming processes, especially since deep learning models require multiple training sessions on high-performance computing systems to optimize model parameters. After training, the model requires validation through cross-validation and independent test datasets to ensure accuracy and stability under various conditions, further increasing time costs. Battery data collection in the field is a real-time and continuous process. Field conditions are variable and uncontrollable, potentially affecting data quality due to noise and interference [69]. Consequently, it is essential to process and clean data in real-time during collection to ensure reliability. This necessitates real-time processing and cleaning of data during collection to ensure its reliability. In comparison to laboratory environments, field data are more diverse and complex, necessitating increased processing time and computational resources. Moreover, the deployment of laboratory-developed models into field applications is intricate and lengthy. Enhancing model adaptability in the field requires continuous updates and retraining to integrate new data and conditions effectively. This process demands significant computational resources and extensive testing and validation in practical scenarios to guarantee model accuracy and stability. Similarly, real-time monitoring of model outputs for field battery diagnostics is time-consuming, necessitating prompt adjustments and maintenance to detect anomalies and faults. As a result, field battery diagnostics involve higher time costs.

To ensure the effective deployment of battery diagnostic technologies in fast-paced industrial environments, optimizing algorithms and hardware resource configurations is crucial. Implementing feature selection and dimensionality reduction techniques can significantly reduce the volume of data processed by machine learning models, thereby lowering computational demands. Additionally, the use of efficient algorithms such as gradient boosting and sparse neural networks not only optimizes processing speeds but also reduces computational complexity. Model pruning and quantization are key techniques for further enhancing efficiency. Model pruning reduces the computational burden by removing redundant or insignificant parameters, while quantization reduces memory usage and accelerates processing speed by lowering the precision of numerical parameters. These techniques effectively minimize the resource requirements of models without significantly sacrificing accuracy. Simultaneously, employing dedicated hardware accelerations, such as GPUs and TPUs enhances the training and inference processes of deep learning models, thereby improving overall efficiency and reducing energy consumption. Furthermore, employing field-programmable gate arrays (FPGAs) and application-specific integrated circuits (ASICs) can significantly alleviate the computational burden on traditional CPU systems [96,97],. FPGAs and ASICs are specially optimized for operations common in deep learning algorithms, such as matrix multiplication, enhancing execution efficiency, reducing energy consumption, and shortening computation times, which are particularly important for real-time battery diagnostics. Effectively managing these optimization processes and finding a balance between model accuracy and resource constraints are key to the successful implementation of AI-driven battery diagnostic technologies. This comprehensive strategy not only improves the practicality and reliability of diagnostic technologies but also helps achieve an optimal balance between cost and efficiency.

3. Outlook

(1). Artificial intelligence for IT operations

Amid the rapid advancements in big data, cloud computing, and AI technologies, machine learning-based battery diagnostic models are facing higher demands for data resources and computational power [100]. The advent of AIOps technology introduces new perspectives and methods for battery diagnostics and life prediction [101]. However, AIOps lacks a precise definition, it is broadly perceived as an emerging technology that merges AI with operational management. AIOps seeks to automate and intelligently manage IT infrastructure using machine learning, data mining, and automation technologies.

In the field of battery diagnostics, AIOps technology, leveraging big data and machine learning algorithms, analyzes operational states, charge-discharge histories, and temperature fluctuations of batteries. This enables timely detection of faults or anomalies, prediction of battery lifespan and remaining usage time, and provision of maintenance recommendations (Fig. 3). This efficient diagnostic and predictive capability helps users quickly identify and resolve issues, thereby enhancing battery system stability and reliability, and achieving the high service quality objectives of AIOps [102]. Furthermore, AIOps technology minimizes downtime and losses due to battery failures by real-time monitoring and predictive assessment of battery conditions [103]. It also provides personalized services and advice, tailoring solutions to the specific conditions of the battery and user needs, thereby improving user satisfaction and experience. On another note, as one of the most widely used products in the energy storage sector of today, batteries incur significant operational and maintenance demands, leading to considerable labor and time costs. AIOps technology is utilized in intelligent battery management to enhance usage and maintenance processes via automation and intelligent workflows. AIOps dynamically tailors charging and discharging strategies based on the operating environment and usage patterns of the battery, significantly extending the lifespan of the battery.

AIOps technology leverages big data and data mining techniques to conduct thorough analyses and extract relevant data regarding battery performance. By examining operational data from batteries, this technology can pinpoint potential problems and areas for optimization, providing crucial support for data-driven decision-making aimed at enhancing battery systems. Furthermore, AI operations technology facilitates cross-platform integration and collaborative optimization. It interfaces with data from various systems and devices, enabling comprehensive management and optimization of the entire energy storage system. This integration includes connections to energy management systems and EV management systems, ensuring detailed monitoring and optimization of energy flows and usage.

(2). Lifelong machine learning

In the field of battery technology, traditional machine learning-based diagnostics often rely on isolated algorithms. These algorithms often do not utilize knowledge from previous similar tasks when tackling battery diagnostic challenges. This approach has significant limitations in addressing rapidly evolving battery performance parameters due to their lack of adaptability and continuous learning capabilities. As the demands for higher efficiency and precision in BMS increase, the deficiencies in accuracy and adaptability of traditional battery diagnostic techniques have become a significant challenge. The introduction of lifelong machine learning presents groundbreaking potential to overcome this challenge [104]. Unlike traditional machine learning methods, lifelong machine learning emphasizes continuous learning and self-optimization throughout the entire lifecycle of the model [105]. This implies that upon completion of initial training, the model can

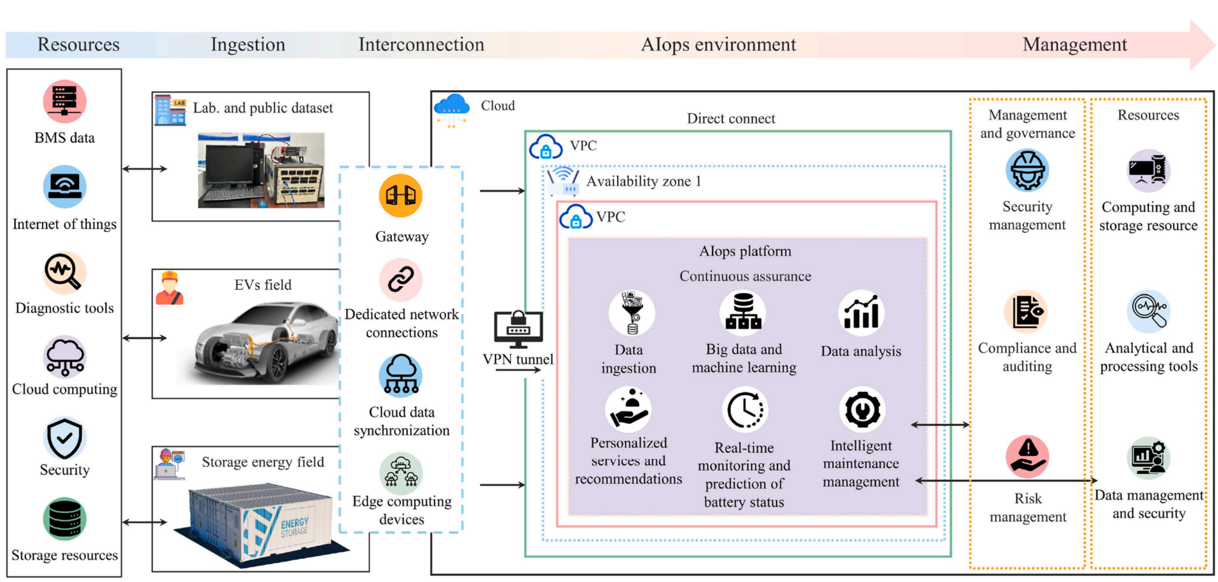

Fig. 3. Battery system maintenance processes based on the AIOps architecture.

continuously adapt to new data and environmental changes. The capability for ongoing learning renders lifelong machine learning particularly well-suited for application in battery diagnostics. Implementing lifelong learning allows for real-time updates of battery diagnostic models to respond to changes in usage frequency, environmental conditions, and aging of battery materials.

Lifelong machine learning technology is pivotal in battery diagnostic systems due to its capability to continually gather and apply learned experiences. Recent advancements demonstrate that combining multiple neural network architectures within hybrid models significantly enhances accuracy, expedites training, and improves the ability to generalize [106]. This approach is effective in transferring learned paradigms across various battery materials and chemistries. For example, it can learn aging characteristics from lithium iron phosphate (LFP) batteries and apply these insights to predict the health condition of nickel cobalt aluminum (NCA) batteries. In battery applications, each usage cycle varies due to factors such as charging conditions, environmental influences, or the physical state of the battery. Lifelong learning models can extract essential information from each usage event, transforming this data into a diagnostic and predictive knowledge base for battery performance This approach enables models to learn and adjust their diagnostic strategies by analyzing data on battery behavior under different temperature and load conditions, thereby maintaining accuracy. Moreover, by continuously monitoring critical performance indicators, including voltage, current, internal resistance, and temperature, lifelong machine learning models not only identify the current health status but also predict future failure points based on historical trends and learning outcomes [107]. This predictive capability substantially enhances preventative maintenance efficiency and battery system reliability of battery systems. In dealing with complex and variable battery usage environments and conditions, lifelong machine learning technology adjusts model algorithms in real-time through its exceptional adaptability (Fig. 4). This adaptability is achieved through continuous online learning, whereby the model continuously updates its weights and parameters upon receiving new data. Furthermore, advanced lifelong learning algorithms, such as elastic weight consolidation, provide a mechanism enabling models to retain previous knowledge while learning new tasks, effectively preventing the overwriting of crucial information during new learning processes (i.e., preventing catastrophic forgetting) [108].

Lifelong machine learning enhances the dynamic learning capabilities and adaptability of battery diagnostic technologies, marking a significant advancement in battery management systems. As data processing and algorithmic techniques evolve, these models will adapt and learn from new data at an accelerated pace. This will improve real-time diagnostic accuracy and health monitoring, ultimately boosting the efficiency, reliability, and safety of battery usage.

(3). Cloud-based digital twins

Amidst the transformation of global energy infrastructure and the rapid growth of the EV market, cloud-based digital twin technology has emerged (Fig. 5). By integrating real-time data with simulation models, this technology creates accurate virtual replicas of physical batteries, delivering actionable insights for enhanced battery diagnostics [109, 110],. As advancements in the internet of things (IoT), big data, and

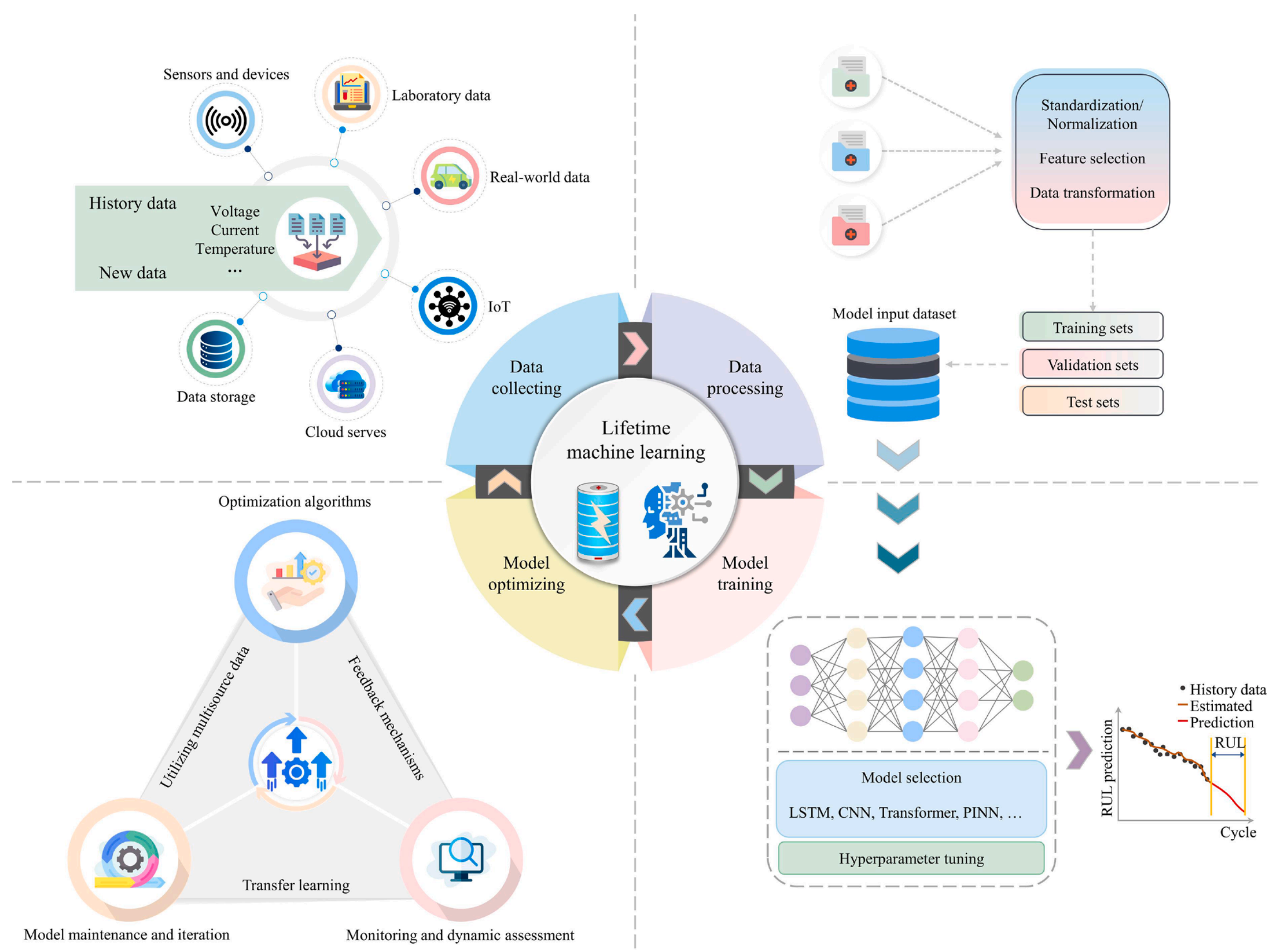

Fig. 4. Real-time model iteration and optimization strategies for lifelong machine learning.

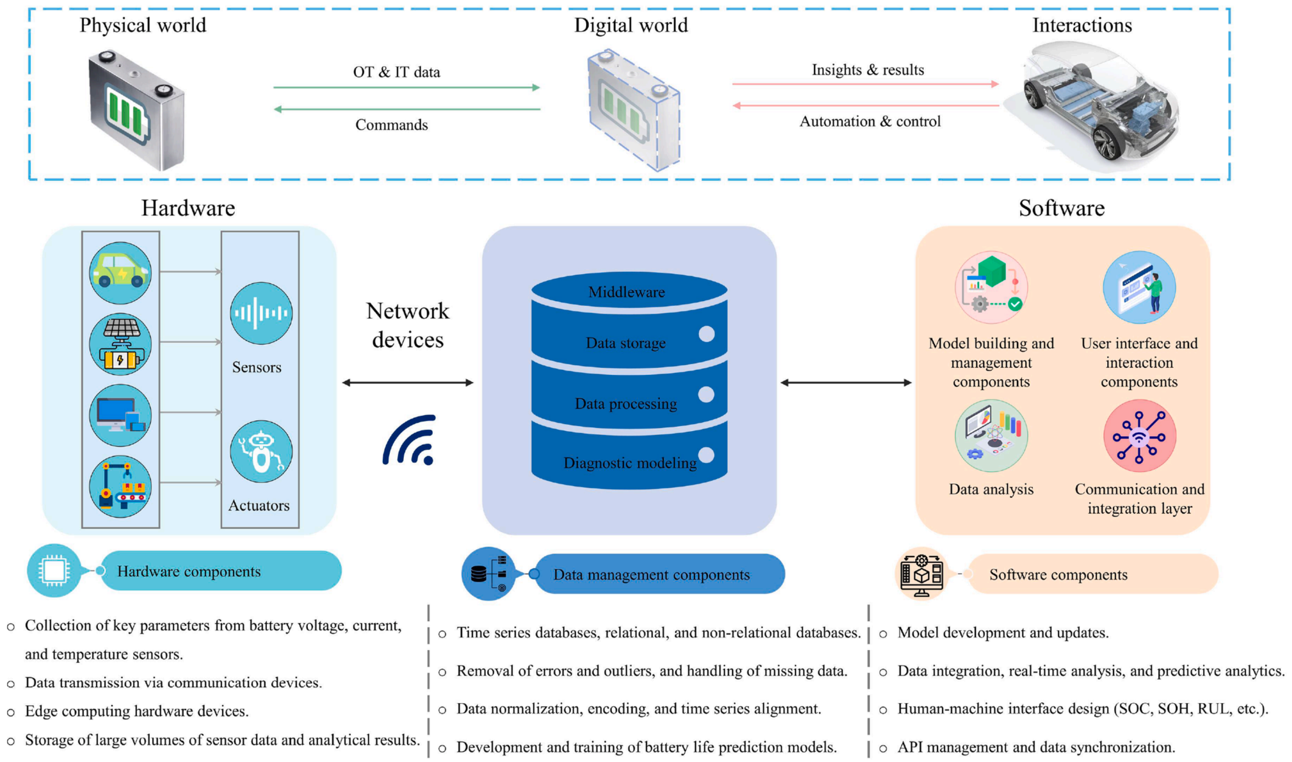

Fig. 5. Digital twin technology in battery diagnostics: a comprehensive perspective from hardware to software.

cloud computing evolve [111-113], an increasing array of sensors will be integrated into battery systems. These sensors deliver multi-dimensional data, including temperature, voltage, and current, significantly improving the accuracy and reliability of diagnostic models [114]. In a recent study, researchers developed a real-time model for estimating the SOH of lithium-ion batteries using digital twin technology [45]. Unlike traditional methods that rely on complete charge-discharge cycles—impractical under dynamic conditions—this model utilizes partial discharge data effectively for real-time SOH estimation. The model introduces an energy difference-aware dynamic time warping algorithm to ensure data structural consistency and comparability across varied discharge processes. Furthermore, the model employs a temporal attention mechanism to assess the importance of each sampling time point, thus identifying critical data segments. The model also utilizes a LSTM network to manage time-synchronized recurrent data for time-series SOH prediction. In the prediction phase, researchers reconstructed data through similarity analysis, using online data matching and reconstruction strategies to forecast future unknown data points. Results indicate that the model consistently achieves SOH estimation error below 1 % across various sampling conditions, affirming its accuracy in real-time evaluation of lithium-ion battery health. This study not only provides a new approach to assessing lithium-ion battery health but also demonstrates the significant capabilities of digital twin technology in processing and predicting real-time data, offering valuable insights for advancing battery management systems. Additionally, we have successfully developed a machine learning model based on cloud battery data aimed at predicting battery failures [115]. By integrating factors across multiple scales and validating with early normal charge voltage and temperature curves, this research shows that the model achieves an accuracy of up to 96.3 %, with an average error of only 7.7 %. These results mark the satisfactory accuracy and reliability of cloud-based battery failure predictions in practical applications.

The performance of cloud computing is critical for deploying cloud-based digital twin technology in battery diagnostics. Cloud platforms provide robust computational capabilities and enable the storage and processing of large data volumes, which are crucial in battery diagnostics and management [116,117],. In this field, cloud computing allows data processing to surpass local hardware limitations. Data from batteries at various locations can be seamlessly integrated through cloud platforms, enabling centralized data processing and analysis. This integration and automation significantly enhance diagnostic efficiency and fault prediction accuracy. This integration and automation markedly enhance diagnostic efficiency and the precision of fault prediction. Moreover, cloud-based digital twin technologies combine AI and machine learning to provide highly intelligent solutions for battery management systems. These advancements not only refine traditional monitoring methods but also significantly improve diagnostic accuracy and efficiency through advanced algorithms. Additionally, integrating AI and machine learning enables digital twin technology to analyze operational data from batteries in real-time, identifying imminent performance declines or potential failures. In summary, cloud-based digital twin technology leverages the extensive computing and storage capabilities of cloud platforms, along with advanced AI and machine learning algorithms, to create a powerful, intelligent, and efficient framework for battery diagnostics and management.

The implementation of cloud-based digital twin technology involves managing extensive historical and real-time data. To facilitate efficient data sharing among stakeholders, establishing standardized and transparent data management methods is crucial. Besides basic security measures such as transport layer security for data transmission encryption and advanced encryption standard for data storage on cloud servers, blockchain technology offers revolutionary security advantages due to its immutable and encrypted nature [118,119],. Integrating blockchain technology into cloud-based digital twin systems can effectively prevent unauthorized modifications and access, ensuring the integrity and privacy of battery performance data. The core features of blockchain, such as cryptographic hashing to link data blocks, guarantee data integrity even after modification attempts [120]. Distributed ledger technology enhances data access permission management for authorized users within the system, increasing transparency and data management accuracy. Furthermore, the decentralized storage mechanism of blockchain improves data stability and security [121]. The use of smart contracts provides automated and precise management tools for data access control, executing contract terms automatically based on predefined rules, thus ensuring proper data use and compliance [122]. Blockchain technology not only secures battery performance data within cloud-based digital twin systems but also significantly enhances system trust and operational efficiency through its transparent and reliable characteristics. This innovative solution offers unprecedented security and efficiency improvements in battery diagnostics and management.

4. Discussion

In EV and stationary power systems, durability and reliability of batteries are critical. The advent of AI has revolutionized battery diagnostics, shifting from traditional model-based methods to data-driven approaches that enhance prediction accuracy. AI-driven diagnostics utilize machine learning models, to analyze data patterns including voltage, current, temperature, and impedance. These models excel at feature extraction, significantly improving health assessment accuracy. Real-time monitoring and predictive analytics are essential for critical applications in electric vehicles and grid storage. These capabilities allow for continual adaptation to new data, significantly improving precision over traditional methods that necessitate regular recalibration. By assimilating varied data sources, AI models offer a holistic perspective on battery health, facilitating the creation of predictive models that reduce risks and limit operational interruptions. However, the effectiveness of AI diagnostics depends on data quality and volume, with poor data risking reliability. Challenges also include the opacity of deep learning models, complicating interpretability, and data security concerns. Future directions involve hybrid models that combine traditional and AI techniques, enhancing explainability and adapting to new battery technologies without full retraining. Continuous advancements in AI and battery chemistry are expected to further sophisticate these diagnostic tools, improving battery safety, efficiency, and longevity. To enhance modeling and forecasting in multiphysics and multiscale systems, particularly those with complex, inhomogeneous cascades of scales, physics-informed learning offers significant potential. This approach integrates prior knowledge from observational, empirical, physical, or mathematical insights into the behavior of battery systems. By incorporating this foundational understanding, physics-informed learning algorithms can more effectively handle real-world physical challenges characterized by incomplete, irregular, or noisy boundary conditions. This methodology not only improves the performance of learning algorithms but also provides a robust framework for tackling intricate dynamic systems with enhanced accuracy and reliability.

5. Conclusions

As the world progresses beyond the foundation of Industry 4.0, it increasingly incorporates advanced technologies such as AI, IoT, sensor technology, and cloud-based innovations. This evolution fosters a symbiotic relationship between humans and machines, aiming to establish a more adaptable and intelligent production environment. In the field of battery diagnostics, machine learning promises to revolutionize real-world applications. Despite relentless progress, modeling and predicting the evolution of nonlinear battery systems using AI-driven technologies inevitably face severe challenges and introduce prohibitive costs and multiple sources of uncertainty. A primary technical obstacle is the opaque nature of deep learning models, often described as "black boxes". In contexts where safety is paramount, this lack of transparency can diminish user confidence and reliance on the results provided by these models. Moreover, these advanced AI models require extensive data and substantial computational power, potentially limiting their widespread deployment in environments where computational resources or data access are constrained. To overcome these limitations and fully leverage the potential of AI in battery management and diagnostics, enhancing collaboration between academia and industry becomes crucial. Such partnerships ensure that research findings are seamlessly transformed into practical technological solutions, fostering an open ecosystem of innovation through knowledge sharing and technological iteration. Additionally, enhancing the transparency and interpretability of AI models is essential. Developing new algorithms or models, such as XAI, can improve the visualization and understanding of decision-making processes, thereby building trust in these technologies. Finally, optimizing the management of computational resources through technologies such as cloud computing and edge computing can enhance data processing and storage efficiency, reduce reliance on local high-performance computing resources, and make technology applications more flexible and cost-effective. Emerging technologies such as AIOps, lifelong machine learning, and cloud-based digital twins will play crucial roles in supporting digital transformation and intelligent progress in battery diagnostics. The growing volume of battery data demands the development of computationally efficient and physically interpretable machine learning models. Therefore, integrating big data analytics with machine learning, coupled with interdisciplinary collaborations, will open new avenues in battery diagnostics. Continuous innovation in AI technologies is essential to drive the global shift towards more intelligent, safer, and efficient battery technologies.

CRediT authorship contribution statement

Jingyuan Zhao: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Xudong Qu:** Writing – original draft, Visualization, Formal analysis. **Yuyan Wu:** Writing – review & editing, Resources, Methodology, Investigation, Formal analysis. **Michael Fowler:** Writing – review & editing, Formal analysis. **Andrew F. Burke:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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