

Review

# Machine Learning-Based Data-Driven Fault Detection/Diagnosis of Lithium-Ion Battery: A Critical Review

Akash Samanta <sup>1,\*</sup> , Sumana Chowdhuri <sup>1</sup> and Sheldon S. Williamson <sup>2,\*</sup><sup>1</sup> Department of Applied Physics, University of Calcutta, Kolkata 700009, India; scaphy@caluniv.ac.in<sup>2</sup> Department of Electrical, Computer and Software Engineering, Ontario Tech University, Oshawa, ON L1G 0C5, Canada

\* Correspondence: akashsamanta440@gmail.com (A.S.); Sheldon.Williamson@ontariotechu.ca (S.S.W.); Tel.: +91-9143877405 (A.S.)

**Abstract:** Fault detection/diagnosis has become a crucial function of the battery management system (BMS) due to the increasing application of lithium-ion batteries (LIBs) in highly sophisticated and high-power applications to ensure the safe and reliable operation of the system. The application of Machine Learning (ML) in the BMS of LIB has long been adopted for efficient, reliable, accurate prediction of several important states of LIB such as state of charge, state of health and remaining useful life. Inspired by some of the promising features of ML-based techniques over the conventional LIB fault detection/diagnosis methods such as model-based, knowledge-based and signal processing-based techniques, ML-based data-driven methods have been a prime research focus in the last few years. This paper provides a comprehensive review exclusively on the state-of-the-art ML-based data-driven fault detection/diagnosis techniques to provide a ready reference and direction to the research community aiming towards developing an accurate, reliable, adaptive and easy to implement fault diagnosis strategy for the LIB system. Current issues of existing strategies and future challenges of LIB fault diagnosis are also explained for better understanding and guidance.

**Keywords:** Battery Management System (BMS); Artificial Neural Network (ANN); Support Vector Machine (SVM); Electric Vehicle (EV); Random Forest (RF); Logistic Regression (LR); Gaussian Process Regression (GPR); cloud-based BMS



check for updates

**Citation:** Samanta, A.; Chowdhuri, S.; Williamson, S.S. Machine Learning-Based Data-Driven Fault Detection/Diagnosis of Lithium-Ion Battery: A Critical Review. *Electronics* **2021**, *10*, 1309. <https://doi.org/10.3390/electronics10111309>

Academic Editors: Zehui Mao, Xinggang Yan and Hamed Badihi

Received: 12 May 2021  
Accepted: 28 May 2021  
Published: 30 May 2021

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



**Copyright:** © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

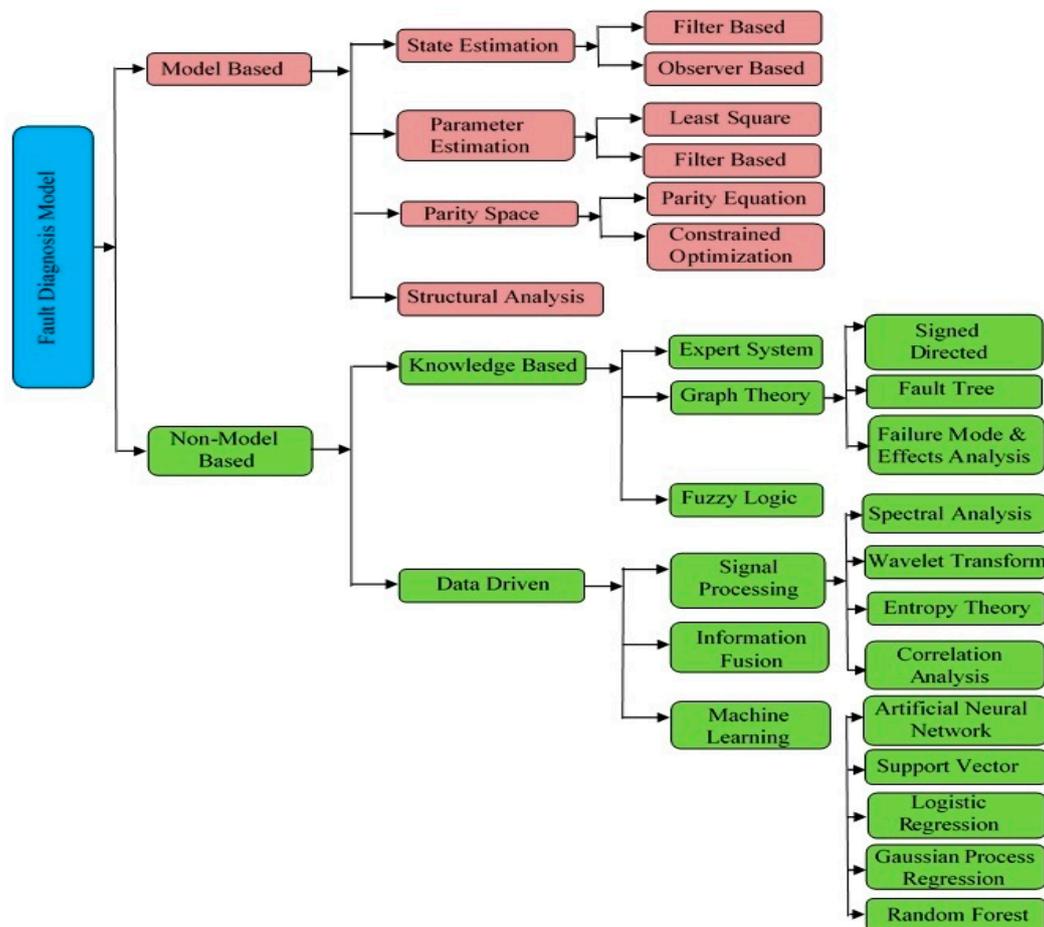
## 1. Introduction

Owing to their high energy density, high power density, long service life, environmental friendliness and low self-discharge rate, lithium-ion batteries (LIBs) have become the prime energy storage system for many applications such as electric vehicles (EVs), grid-level power storage and several other consumer electronics [1,2]. However, the safe and reliable operating area of the LIB is very narrow, which necessitates a battery management system (BMS) for effective operational control, protection and energy management [3–7]. In addition, due to the limitation of the cell voltage and storage capacity of a single LIB cell, high power applications of LIBs such as EVs and grid-tied energy storage systems require hundreds or even thousands of single battery cells [8]. Cell inconsistencies in a LIB pack are a common issue; thus an appropriate BMS is also indispensable for the safe and reliable operation of the LIB pack as well as every single cell of the battery pack [9,10]. A BMS can be designed to serve many functions including but not limited to data acquisition, estimation of the state of charge (SOC) [11,12] and state of health (SOH) [13,14], temperature measurement/estimation [15], cell balancing [16,17], fault detection/diagnosis [18,19] and thermal management [16]. Very recently researchers have started paying attention to the detection/diagnosis of faults after the occurrence of several accidents in e-transportation due to the failure of the LIB system [20,21]. It was evidenced that extreme operating conditions, manufacturing flaws and battery aging were among the prime reasons behind the battery system failure.

The performance of LIB is affected by different abusive operating conditions such as overcharge or over-discharge event, startup at low temperature, vibration and higher heat generation resulting in metallic lithium plating, formation of solid electrolyte interphase layer and formation of lithium dendrite that eventually accelerate the aging of LIB and may lead to catastrophic failure during operation [22–24]. Therefore, the presence of fault detection and diagnosis features of BMS is highly critical for LIB-powered systems, especially for high-power applications. Smarsly et al. [25] demonstrated that a minor fault could eventually result in dangerous consequences without proper fault diagnosis and defense mechanism. Relevant discussion on the importance of fault diagnosis and defense mechanisms was also presented by Williard et al. in references [26] and [20]. Studies on LIB fault mechanisms that tried to find the causes and consequences of LIB faults have been extensively reported in the literature. Research on LIB fault detection and diagnosis has gained momentum in the last few years. Faults in the LIB system are typically classified as internal and external faults. Some of the most frequently reported external faults are cell wiring faults, faults in the thermal management system and sensor faults such as temperature, voltage and current sensor faults, whereas some common internal battery faults are overcharged, over-discharged, internal short circuit (ISC), accelerated degradation and thermal runaway. Tran et al. [19] presented a detailed classification of the commonly reported LIB faults. A few other studies also classified the LIB faults from control system perspectives [27]. They grouped the overcharged, over-discharged, overheating, external short circuit (ESC), ISC, electrolyte leakage, battery swelling, battery accelerated degradation and thermal runaway faults as battery faults. On the other hand, the voltage, current and temperature sensor faults were grouped under the sensor faults and the terminal connector fault, cooling system fault, controller area network (CAN) bus fault, high voltage contactor fault and fuse fault were included under actuator faults.

Realizing the importance of fault detection/diagnosis for the safe and reliable operation of LIB, a significant number of research studies were conducted aiming towards developing an accurate, reliable, robust and easy to implement fault diagnostic strategy. Lu et al. [28] briefly illustrated the reason why the development of an effective fault diagnosis system is crucial for the advancement of LIB-powered systems. Special concentration on the sensor fault diagnosis was provided by Xiong et al. [18]. Lyu et al. [29] presented a detailed discussion particularly on the failure mechanism of LIB and its possible solutions through a state-of-the-art review study. Fault diagnosis methods reported in the literature can be broadly categorized into model-based and non-model-based methods. However, a fusion of these two categories is also reported. A detailed classification of LIB fault diagnosis methods is presented in Figure 1.

It is noticed from the literature that model-based and signal processing-based methods have been most extensively used for the LIB fault detection among the fault diagnosis methods mentioned in Figure 1. Machine Learning (ML)-based techniques were very recently adopted; however, they are increasing at a much faster pace owing to some of the prominent advantages such as a high level of accuracy, compatibility with the highly nonlinear LIB system and reduced dependence on domain experts. The accuracy and reliability of model-based fault diagnostic strategies predominantly depend on the accurate equivalent circuit model (ECM) of LIB. Obtaining a highly accurate model is challenging as the internal characteristics of the highly nonlinear LIB are still not fully understood. This limitation is eliminated with the advent of ML-based techniques. Furthermore, the impacts of measurement noises that limit the application of signal processing-based methods are also reduced to a significant extent with the deployment of ML-based techniques. Moreover, ML-based techniques further simplify the fault diagnosis by eliminating two complex and time-consuming steps: Collecting the battery's accurate physical information and learning the nonlinear correlation between battery internal parameters and external measured parameters such as operating current, terminal voltage and temperature. These eventually reduce the requirement of domain-specific knowledge, time and the cost of the system development.



**Figure 1.** Classification of LIB fault diagnosis methods.

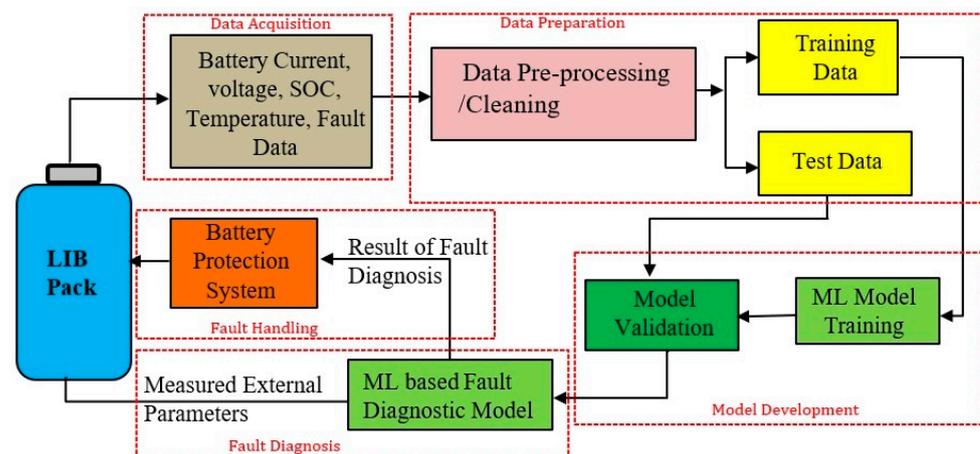
Recently, Hu et al. [30] and Tran et al. [19] presented an overview of different fault diagnosis algorithms for the LIBs. The concept of dependable graph-based fault tolerance and diagnostics has been explained by Ubar et al. in references [31–33]. Reza [34] conducted a review study focusing on the application of ML approaches in the BMS of LIBs. However, an in-depth review exclusively on the state-of-the-art ML-based fault detection/diagnosis techniques has not yet been reported in the literature. Moreover, the existing review studies primarily focused on the general issues and challenges in LIB fault diagnosis. They are often lacking in explaining the challenges and limitations of any specific diagnostic strategy. A detailed discussion on the current challenges that researchers are facing and the research gaps that need to be addressed exclusively in the area of ML-based fault diagnosis has not yet been covered in the existing literature. Therefore, realizing the promising future and prominent advantages, the ML-based data-driven fault diagnosis techniques are exclusively reviewed in this article alongside highlighting the current issues, challenges and future research scope. The primary objective of this review study is to provide a ready reference and direction to the researchers towards developing an accurate, efficient, reliable and easy to implement ML-based data-driven fault diagnostic method for the LIB system. A detailed classification of specifically ML-based approaches that are currently being used in the BMS of LIB is presented in Section 3.

The remaining portion of the review article is organized as follows. The fundamentals of ML-based LIB fault diagnosis methods with a special focus on generic methodologies are presented in Section 2. Section 3 provides an overview of different kinds of ML-based fault diagnosis techniques typically employed by researchers so far. Section 4 is the prime section of this review article as it provides a comprehensive survey on the ML-based LIB fault diagnostic techniques reported in the literature. Section 5 summarized the current

issues, challenges and future research scopes in the LIB fault diagnosis. Finally, concluding remarks are presented in Section 6.

## 2. Genetic ML-Based LIB Fault Diagnosis Scheme

The protection of LIB packs and minimizing the risks associated with the operation of LIB-based systems are indispensable in BMS. Therefore, detection/diagnosis of faults in LIB systems and designing an effective defense mechanism are of utmost importance. Naturally, to establish an appropriate fault diagnostic strategy, in-depth knowledge and understanding of different kinds of faults alongside the corresponding fault mechanism in LIBs are highly essential. Regarding these, Lyu et al. [29] presented a detailed review of failure modes and mechanisms of LIBs and Hu et al. [27] presented a comprehensive review of fault mechanisms, fault features and fault diagnosis of various faults in LIBS, including internal battery faults, sensor faults and actuator faults. A summary of different kinds of external and internal faults in LIBs along with an overview of major fault diagnostic strategies were presented by Tran et al. [19]. Before diving into the details of ML-based fault diagnostic methods reported in the literature, it is worth giving an introduction to the subject matter for the basic understanding of the readers. Therefore, in this section, a generic ML-based fault diagnosis scheme for LIB is presented. Figure 2 depicts the generic block diagram of the ML-based fault diagnosis scheme.



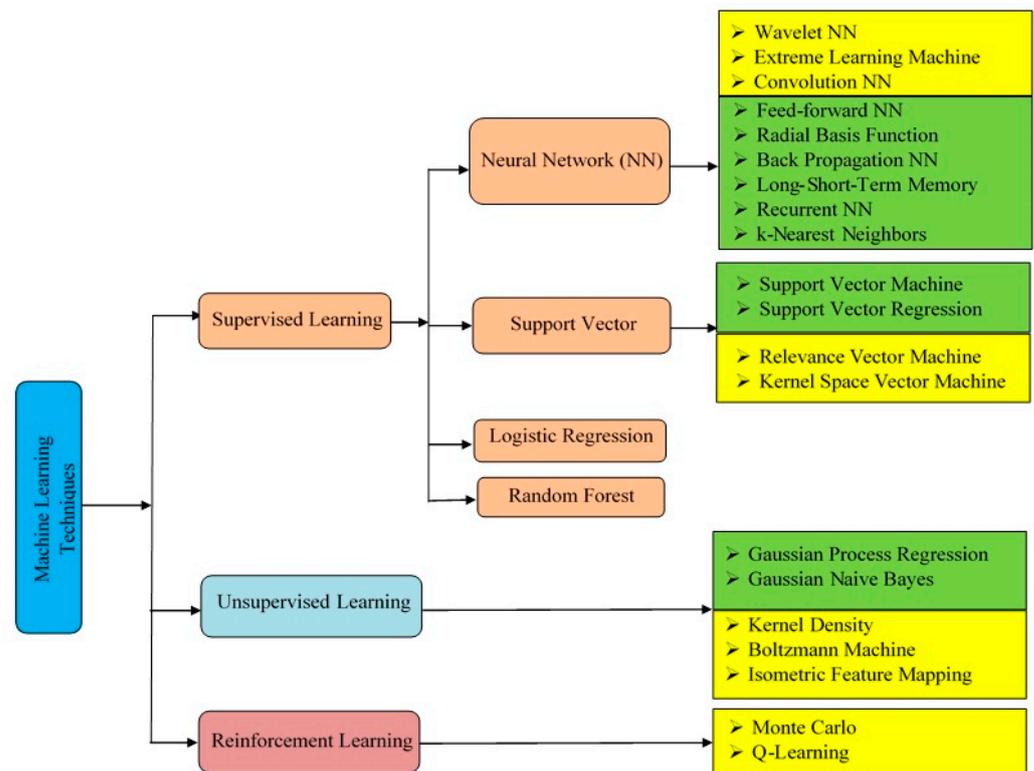
**Figure 2.** Generic block-diagram of ML-based fault diagnosis scheme.

Typically, the voltage, current and temperature of the battery cells are recorded using sensors and a data acquisition system. Further, data is also generated by analyzing the consumption pattern and through experiments. Battery fault data is collected from battery operations data and also through laboratory experiments. Then the raw data is pre-processed for cleaning and feature extraction. Then the data is divided into a training data set and a test data set randomly. While formulating an ML-based fault diagnostic strategy, the training data set is used for learning purposes, whereas the test data set is used for validation. Finally, the measured battery parameters such as operational current, terminal voltage, temperature and others are used to detect battery faults using the validated ML-based fault diagnosis scheme. This fault detection signal is further used as a command to the battery protection system. So far, five ML approaches have been reported in the literature to develop the ML-based fault diagnostic scheme; however, in general, apart from the ML algorithm, the rest of the steps and components are very much similar. These five ML algorithms are discussed briefly in the subsequent section.

## 3. Overview of ML-Based Fault Diagnosis Techniques

Currently, ML techniques are extensively used in the BMS of LIBs. A summary of ML approaches in BMS is presented by Reza et al. through a review study [23]. Here, this

section aims to provide an overview of different ML techniques that are currently being used in BMS applications specifically for LIB fault diagnosis. A complete family of ML approaches that are successfully used in BMS of LIB is illustrated in Figure 3. Among all these, the ML approaches that were already employed for the LIB fault diagnosis are highlighted in green color, whereas the remaining potential approaches are highlighted in yellow for the readers' convenience. A brief description of each ML-based fault diagnosis technique as mentioned in Figure 3 is presented below.



**Figure 3.** A complete family of ML approaches, used in BMS of LIB.

### 3.1. Artificial Neural Network

Artificial Neural Network (ANN) is one of the most widely used frameworks of ML algorithms to perform a wide variety of tasks [35,36]. It is inspired by the biological neural networks that constitute animal brains. ANN uses supervised learning approaches during model training. Features like self-adaptability and learning abilities of the animal brain enable ANN to perform tasks by considering examples, generally without being programmed with task-specific rules. Moreover, ANN is capable of effectively capturing the dynamics of a highly nonlinear system. All these features make it suitable for LIB due to its highly complex and nonlinear dynamic characteristics. The basic strategy is to form a nonlinear black-box of an ANN-based fault diagnosis model by learning implicit rules from known pairs of input and output data, then to validate the model by test input and output data that are unknown to the model. The training is typically conducted offline. Then the ANN model can effectively distinguish between the normal and abnormal conditions of the battery system provided the ANN model is well-trained with a sufficient amount of data. There are several variants of ANN that can be broadly classified into two subgroups. The classic neural networks subgroup includes wavelet neural network (WNN), back-propagation neural network (BPNN), radial basis function network (RBFN), feed-forward neural network (FFNN) and extreme learning machine (ELM). On the other hand, modern neural networks are often recognized as deep NNs, which mainly include recurrent neural networks (RNNs) and convolutional neural networks (CNNs). Often a combination of one of these techniques is also used in BMS applications such as long

short-term memory network (LSTM) and RNN-LSTM. Here, LSTM is an expansion of RNN and CNN; similarly, RNN-LSTM is a combination of RNN and LSTM. There are several other variants of ANN that were discussed in detail by S. Walczak [37]. However, among these ANN-based techniques only basic ANN, LSTM, RNN, RNN-LSTM, and few other hybrid techniques have so far been used for fault detection of LIBs as mentioned in Figure 3.

### 3.2. Random Forest Classifier

Like ANN, Random Forest (RF) classifier is also a supervised ML approach that has demonstrated satisfactory performance while employed in various classification problems such as sleep stage classifications from electroencephalography (EEG) data [38], bearing fault identification from vibration data [39], facial expression detection from video data [40], crop type classification from hyperspectral images [41], lung vessel segmentation from computed tomography (CT) images [42] and many more [43,44]. RF uses the multiple numbers of trees of slightly different structures that are collectively employed for classifications. Collaboration among trees in RF makes the model more robust compared to any single classifier typically used in other statistical classification problems [45]. RF is a linear classifier with reduced computational complexity when compared to some other popular classifiers, making it suitable for lightweight algorithms for real-time operation [46]. Moreover, the scaling of the features is highly convenient and the parallel operation of the algorithm alongside the primary usage of the system is not an issue as well.

### 3.3. Support Vector Machine

Despite the requirement of highly complex quadratic programming, the Support Vector Machine (SVM) is increasingly used for solving classification and regression problems in recent times [44,47]. SVM tries to form different data clusters by constructing hyperplanes in high dimensional space in order to distinguish a different class of data while dealing with classification problems. The typical criteria for finding optimal separation boundaries are to maximize the distance between the hyperplane and the nearest data point of any cluster. SVM is becoming a powerful tool for regression analysis in highly nonlinear systems like LIB. The use of SVM in regression is also termed Support Vector Regression (SVR). SVR uses different kernel functions and regression algorithms to transfigure a nonlinear model into a linear model for ease of analysis. There is also another variant of SVM, namely, kernel space vector machine (KSVM). Further details of SVM can be found in reference [48]. Like ANN, SVM-based fault diagnostic techniques also do not require an equivalent battery model. SVM is also a supervised ML approach. So far, only SVR and SVM have been used for fault diagnosis of LIBs in this category.

### 3.4. Gaussian Process Regression

Gaussian Process Regression (GPR) is an unsupervised ML technique. The two primary goals of this technique are clustering the data into groups by similarity and dimensionality reduction to compress the data while maintaining its structure and usefulness of data. GPR also uses kernel-based ML approaches which can discover prognostics by leveraging prior knowledge based on the Bayesian model. Thereafter, it utilizes the variance around its mean prediction to provide information about the associated uncertainty in the system. So far very few studies have used GPR for LIB fault diagnosis.

### 3.5. Logistic Regression

Logistic Regression (LR) is a statistical classification technique used to classify observed data based on the pre-defined criteria [49,50]. This method is the simplest method for two-class classification and has shown very good performance in linear and nonlinear regression. However, so far very few researchers have employed LR for fault detection/diagnosis in the LIB system [51].

#### 4. Review of Fault Diagnosis Methods and Comparative Analysis

In the previous section, an overview of ML approaches that are used to detect different types of LIB faults is presented. Now, an in-depth review of ML-based fault diagnostic methods as reported by various researchers in the literature is presented in this section. Research studies are grouped based on the kind of algorithms used as discussed in Section 3. Finally, a comparison study among these techniques is also conducted at the end of this section in Table 1.

**Table 1.** Comparative analysis among ML-based LIB fault diagnosis methods.

Diagnosis Methods	Major Advantages	Major Limitations	Comments on Practical Applicability
ANN	<ul style="list-style-type: none"> <li>• Insensitive of the model uncertainty</li> <li>• High Accuracy</li> <li>• Highly capable to capture the nonlinearities of LIB</li> <li>• Adaptive to temperature and other uncertain factors</li> <li>• Easy to implement in hardware</li> </ul>	<ul style="list-style-type: none"> <li>• Modeling is complex especially for models having a large number of hidden layers and many input features</li> <li>• Time-consuming</li> <li>• Generalization irrespective of battery and working conditions is difficult</li> <li>• A large amount of training data thus large memory requirement to store the data and algorithm</li> </ul>	To date, the most frequently employed ML technique for LIB fault diagnosis. Accumulation of fault data and further development could enable ANN-based methods suitable for practical applications
RF	<ul style="list-style-type: none"> <li>• High classification ability</li> <li>• Low computational cost</li> </ul>	<ul style="list-style-type: none"> <li>• High quality and volume of battery fault data is required</li> </ul>	Suitable for real-time prediction, however, accuracy and reliability are the major concerns for practical application. So far, very few studies have been conducted, thus it is too early to judge the practical applicability
SVM	<ul style="list-style-type: none"> <li>• High Accuracy</li> <li>• Less complex modeling compared to ANN</li> <li>• Highly capable to capture the nonlinearities of LIB</li> <li>• Less training data required compared to ANN</li> <li>• Faster diagnosis</li> </ul>	<ul style="list-style-type: none"> <li>• Data preprocessing is time-consuming and complex</li> <li>• Selecting appropriate kernel function and fine parameter tuning is challenging</li> <li>• Model adaptability and reliability is a concern</li> </ul>	Good quantity and quality of training data including fault data with sufficient proficiency in modeling could enable this method suitable for practical application
GPR	<ul style="list-style-type: none"> <li>• Good accuracy</li> <li>• Non-parametric; Being flexible</li> <li>• Provide covariance to generate uncertainty level</li> </ul>	<ul style="list-style-type: none"> <li>• Effectiveness is highly sensitive to kernel functions selection which is complex and required expertise</li> <li>• High computational complexity</li> </ul>	So far, very few studies have been conducted, even GPR is not directly used for fault diagnosis, thus it is too early to judge the practical applicability.
LR	<ul style="list-style-type: none"> <li>• Good accuracy</li> <li>• Easy to implement</li> </ul>	<ul style="list-style-type: none"> <li>• Accommodating a large number of the feature vector is challenging</li> </ul>	Too early to judge the practicability as the Model adaptability, generalization capability, accuracy, and reliability in the real-world system have not yet been tested.

##### 4.1. ANN-Based Fault Diagnosis Methods

Among other ML-based fault diagnostic methods, ANN-based techniques have been used most extensively by researchers. Gao et al. [52] used a single hidden layer BPNN approach to detect four types of critical faults, namely, voltage sensing fault, temperature sensing fault, battery cell fault and ESC fault through online monitoring of the measurable parameters (e.g., voltage, current and temperature). Here, Genetic Algorithm (GA) was used to initialize and optimize the connection weights and thresholds of the neural network

(NN). Comparative analysis indicated that the fusion of GA and BPNN improved the fault diagnosis performance compared to conventional BPNN. However, no insight into the practical application of the fault diagnosis method was presented in this study. On-line diagnosis and fault handling were not covered as well. The reported prediction error of GA-BPNN is around 2% which may not be acceptable to some of the real-world applications. The sophisticated and high-power applications essentially demand very high prediction accuracy. Very few data were used for training and testing purposes by the researchers; thus, the reliability of this strategy in real-world applications needs to be examined. A similar study was conducted by Sbarufatti et al. [53] where Particle Filters (PF) were employed for parameter identification instead of GA and the fault diagnostic model was implemented based on radial basis function neural networks (RBF-NN). This method was designed to provide over-discharge protection by predicting the end of discharge of LIBs through real-time measurement of the terminal voltage. The PF was used to identify the model parameters in real time as soon as new observations of the battery terminal voltage became available. This approach made the method adaptive to anomalous behaviors due to failures or unforeseen operating conditions. This adaptive fault diagnostic method enhanced the prediction accuracy and reliability of parameter identification over the GA-BPNN-based method. However, the data used during modeling were recorded based on the constant current charge–discharge test instead of actual vehicle operating data or data generated through the standard drive cycle test. Therefore, the robustness and reliability of the diagnostic method in a real-life scenario need to be further explored.

Actual vehicle operating data for a whole year were utilized by Zhao et al. [54] to introduce a big data-driven fault diagnosis model powered by an ML algorithm and a  $3\sigma$  multi-level screening strategy ( $3\sigma$ -MSS). The  $3\sigma$ -MSS was utilized to detect the fault based on abnormal changes in cell terminal voltages in a battery pack and NN was employed to fit the cell fault distribution in the battery pack. According to the researchers, this  $3\sigma$ -MSS-NN-based fault diagnosis strategy can also see the design flaws in battery systems by analyzing the abnormalities hidden beneath the surface which can be utilized as feedback to the manufacturers and designers for further upgrade. The effectiveness of the  $3\sigma$ -MSS-NN-based diagnosis method was verified by comparing the model outcomes with the results yielded by the local outlier factor (LOF) algorithm and clustering outlier diagnosis (COD) algorithm as well as with the actual vehicle data. The model seems very effective and is expected to provide reliable predictions in a real-world system. However, the major limitation of this method is that it requires an extended period and large sample size to develop a reliable diagnosis model, which is costly and laborious. Often access to real-life data is also restricted, especially fault data. Gao et al. [55] designed a self-recovery real-time battery fault diagnosis scheme for EVs and also developed a prototype in hardware. The system can diagnose and protect an EV battery pack from over-charge, over-discharge, over-current and over-temperature conditions by utilizing sensor recorded data. Despite satisfactory performance, the fault diagnosis scheme was developed for a 12 cell LIB pack. Installing one temperature sensor per cell for temperature measurement is feasible for a prototype system; however, it is impractical for real EV applications due to cost, system weight and space limitations. Moreover, the impacts of environmental factors and cell aging were not considered while developing the diagnostic model which will significantly affect the system performance in a real-world application.

The concept of the deep-learning-enabled fault prognosis method was introduced by Hong et al. [56] where long short-term memory (LSTM) recurrent neural network (LSTM-RNN) was used for multi-forward-step voltage prediction to determine the advent of battery faults and mitigate runaway risk. To ensure the prediction accuracy and model robustness, a high volume of real-world operational data of an electric taxi was used. Alongside the influence of the weather and driver's behavior on the LIBs, the performance was also considered. The effectiveness, accuracy of voltage prediction and model robustness were assessed through seasoning using cross-validation and comparative study among different hyperparameters besides a comparison with actual operational data. Despite high

accuracy, parameter optimization is a very tedious and time-consuming task as each LSTM model has its multiple structure parameters. Therefore, learning the battery characteristics under certain operating and environmental uncertainties is challenging in a short time, and training the LSTM model using a small amount of test data affects the prediction accuracy. This fact makes it more difficult to achieve a universal model that could accurately predict the state of multiple battery parameters regardless of battery aging, variations in road conditions, changes in driver's driving behavior, and other uncertainties in environmental and operating conditions. Ortiz et al. [51] conducted a comparative study to demonstrate the effectiveness of five commonly used algorithms, namely, k-nearest neighbors (k-NN), LR, Gaussian naive Bayes (GNB), KSVM and NN, to classify the unbalanced and damaged Ni-MH battery cells. While this test was not conducted for LIB cells, this study showed that the NN-based diagnostic tool provides a high evaluation score with correctly classified data. A similar detailed comparative study for LIBs will be highly appreciated.

#### 4.2. RF Classifier-Based Fault Diagnosis Methods

While RF has been used for a range of classification problems for the last few decades, the application of RF for the LIB fault diagnosis has only been very recently introduced. The overwhelming demand for computationally inexpensive prediction algorithms suitable for real-time operation and easy to implement in low-cost hardware necessitates the employment of RF for efficient fault diagnosis in LIB systems. Yang et al. [57] primarily proposed a fractional-order model (FOM) and a first-order Resistance Capacitance (RC) model to determine the ESC fault in LIB where model parameters were identified by the GA. Further, they have used an RF classifier to identify cells with electrolyte leakage that typically occurs due to ESC faults. Later on, Naha et al. [58] used the RF-based fault diagnosis model for online detection of ISC in LIB cells. The authors generated the training feature set by developing two ECMs of LIB with and without an ISC where ECM parameters were identified and extracted from several charge–discharge cycle tests. According to the study, the fault detection accuracy is 97%; however, the major concern is that in several advanced highly sophisticated and high-power applications even this 3% inaccuracy is unacceptable. The change in the internal resistance of LIB is considered as one of the prime factors to determine ISC in this method. Now as the internal resistance of LIBs is itself very small, the change in internal resistance during ISC is also negligibly small, especially in the high SOC region. Therefore, accurate and precise determination of that small change in the internal resistance is highly challenging. This will eventually reduce the effectiveness and reliability of the focused fault diagnostic method.

#### 4.3. SVM-Based Fault Diagnosis Methods

Inspired by the satisfactory performance while predicting important states such as SOC, SOH and remaining useful life (RUL) of LIB, SVM has very recently been introduced into the domain of intelligent fault diagnosis of LIBs. In 2021, Yao et al. [59] employed SVM to identify the fault state and the degree of fault. In addition, the discrete cosine filtering method based on white noise characteristics and the grid search method were used to enhance the prediction accuracy and reliability of SVM-based diagnostic scheme. A fusion of the discrete cosine filtering method and grid search method with SVM was used to diagnose the connection fault of series-connected LIB cells in a battery pack. Specifically, the discrete cosine filter method was employed to reduce the influence of measurement noise during prediction. The authors used a modified covariance matrix (MCM) of filtered data, an up-gradation of the traditional covariance matrix (CM), to reduce the influence of current measurement noise on the condition indicators. Furthermore, to enhance the accuracy and the robustness of SVM-based diagnostic method, the grid search technique was employed to optimize the kernel function parameter and the penalty factor. This method demonstrated highly satisfactory performance; however, the state identification is very time consuming. According to the study, the minimum time requirement is around 167 s, which limits the practical viability of the strategy for online fault diagnosis. The

impact of cell aging and temperature variation on cell parameters was not considered while recording the experimental data. This will lead to inaccurate prediction in a real-world application where LIB is subjected to different weather conditions and cell aging is inevitable. The fault diagnosis accuracy of GS-SVM as reported in the study was 95%. However, 5% inaccuracy in fault diagnosis for several high voltages and current applications such as e-transportation systems and power grid applications is not permissible from a safety point of view. Therefore, further research is required to make the model adaptive to aging and other environmental changes alongside enhancing the prediction accuracy acceptable to high-power applications. Advancement is also required to make the model suitable for real-time prediction with an improved level of diagnosis efficiency and reliability. In another study conducted by Hashemi et al. [60], while SVM was not directly employed for fault diagnosis, a fusion of SVM and GPR termed machine learning parameter estimator (MLPE) was used for ECM parameter estimation of LIB. Thereafter, the fault diagnostic strategy is very similar to other ECM-based fault diagnostic methods such as residual generation and comparison with normal operating states. This multiple model adaptive estimation (MMAE) was designed to detect the overcharge (OC) and under-discharge (UD) fault conditions in LIB. This study only focused on the OC and UD faults of LIB; however, several other fault conditions may also be very severe in practical applications. Thus, a similar diagnostic approach for other faults must also be developed. Data used during modelling and validation was collected by subjecting each battery cell with step load variation instead of standard drive cycle loading. Step load variation is far from the battery loading in real-world systems such as load profile of an on-road EV battery. The impact of temperature and SOC variation was only considered but the influence of cell aging was not considered. The major limitation of the model is the generalization. In order to detect the OC and UC faults, the ECM parameters of each cell need to be subjected to the OC and UC faults. Therefore, extensive experiments need to be conducted for data collection, which is complicated, time-consuming and requires a highly safe laboratory setup. The generalization of the model is also challenging. There are two other variants in the support vector domain, namely, KSVM and relevance vector machine (RVM), that are also reported in the focused domain. Ortiz et al. [51] employed KSVM for classifying faulty and non-faulty battery cells and revealed that the KSVM method has a greater classification efficiency compared to conventional SVM. This is especially because the characteristics and the operations of the battery cell can be better adapted by the function of the radial base kernel. However, the performance of the KSVM-based method was not tested for LIB, which needs to be further explored. Despite RVM being extensively used for predicting the RUL of LIBs [61–63], it is not yet employed for LIB fault diagnosis.

#### *4.4. GPR Based Fault Diagnosis Methods*

In recent years, numerous efforts on diagnosis and prognosis of faults in LIB have been provided; however, the potential of GPR has not yet been deeply explored. In reference [64] Tagade et al. used GPR for degradation mode diagnosis in LIB. In reference [51] Ortiz et al. evaluated the classification efficiency of five different supervised ML methods where Gaussian naïve Bayes (GNB) is one of the methods employed for the LIB fault detection. The study showed that each method has its advantages over others where GNB demonstrated high efficiency in classifying battery cells that are unbalanced and damaged. The fundamental concept behind the GNB-based classifier is to build a non-linear smooth curve differentiating between the faulty and non-faulty cells based on the occurrence probability of events. The performance of GPR in diagnosis and prognosis in LIB was demonstrated by Zhang et al. [65]. They used over 20,000 electrochemical impedance spectroscopy (EIS) spectra to identify degradation patterns where GPR is used to accurately estimate the capacity and predict the RUL that are key indicators of the battery SoH. In this study, GPR is not directly used for fault detection/diagnosis in the LIB system. Moreover, recording training data for ML models through EIS is a complex procedure, is time consuming and

requires the involvement of domain experts. Either way, significant further research is required to develop a GPR-based fault diagnostic model for the LIB system.

#### 4.5. LR-Based Fault Diagnosis Methods

Ardeshiri et al. [34] first-ever utilized LR for the fault diagnosis in a battery system. Alongside high accuracy, Ardeshiri et al. showed that the LR algorithm is the easiest algorithm to set up and has a good overall performance when compared to four other ML-based fault diagnostic techniques, namely, k-NN, GNB, KSVM and classical NN. In this study, the influence of different uncertainties in real-world applications was not considered while accumulating model training and testing data. Therefore, despite high accuracy and ease of implementation as indicated by these researchers, significant further research and development are required before the practical implementation of the proposed LR-based method.

### 5. Issues, Challenges and Future Research Scopes in LIB Fault Diagnosis

A detailed discussion on the ML-based detection/diagnosis of different kinds of internal and external faults in LIB is presented in Section 4. It is evidenced that researchers have proposed several strategies for the LIB fault diagnosis and they have made considerable progress on providing safety concerning the LIB system. However, to develop a robust, reliable, efficient battery fault diagnosis strategy suitable for real-world applications, significant further research is still required to address several limitations and to meet future requirements. The current issues in LIB fault diagnosis along with the future research scopes and recommendations to the research community are discussed in this section. To give readers a better understanding, the current issues and future research scopes are grouped into three categories: Those related to LIB fault diagnosis in general, those related to specifically ML-based diagnostic strategies, and those related to the system requirement and practicability.

#### 5.1. Current Issues and Research Scopes Related to LIB Fault Diagnosis in General

The existing literature is lacking in providing a unified understanding of all kinds of battery fault mechanisms for the wide range of LIB cells. Researchers have explored only a limited type of LIB fault so far and several battery faults are still not fully understood. The lack of understanding of the fault behavior affects the effective determination of fault thresholds for accurate detection as well as prognosis of faults, which leads to a false alarm, missed detection and time delay in fault detection. Most of the studies used fixed threshold or double-threshold; however, batteries are exposed to adverse operating and environmental conditions alongside the natural aging process, which influences the battery characteristics. The concept of adaptive threshold has not yet been deeply explored. Some of the ML approaches have proven an adaptive capability that could be properly deployed through further research to meet the requirement of complex real-world scenarios and to obtain a reliable fault diagnostic method powered by ML techniques. The increasing necessity and demand of fast charging of LIB, especially in EVs, require a solid understanding of the degradation mechanism under fast charging conditions. Significant progress is required to develop a real-time fault diagnosis and prognosis strategy for the LIBs that use fast charging. Furthermore, it is noticed from the literature and practice that effective charge equalization in any operating condition is crucial for maintaining the safety of LIB. The effective charge equalization depends on the real-time monitoring of battery parameters and the precise estimation of charge. Several cell balancing schemes and ML-based charge estimation methods were proposed in the literature; however, the interrelation among precise determination of cell imbalances, effective cell equalization and the fault detection of LIB has not yet been deeply explored. Often ML-based strategies use real-time monitoring and deterministic methods to obtain different parameters of LIB such as temperature, terminal voltage and current for fault detection/diagnosis. However, a fault prevision method powered by ML techniques could be more useful instead of deterministic and

real-time monitoring. That needs further attention from the researchers. While ML-based strategies are extensively used for predicting the RUL of LIB, the interrelation between RUL and fault prediction using ML needs to be investigated. It is also anticipated that an ML-based constant monitoring system could be the one that better faces the safety constraints in LIB. Despite few research studies in the medical field [66,67], it has not yet been investigated in the LIB domain. Therefore, further research is recommended here as well.

### *5.2. Current Issues and Research Scopes Related to Specifically ML-Based Diagnostic Strategies*

In spite of several advantages, two major limitations of ML-based fault diagnosis strategies are the time-consuming training process and the requirement of a high volume of battery data, especially fault data. Almost in all high-power applications, hundreds and even thousands of individual LIB cells are connected in series and parallel configurations to obtain desired voltage and current level. The accuracy and reliability of data-driven ML-based fault diagnosis methods extensively depend on the quantity and the quality of battery data. Existing studies mostly used a very limited quantity of data and recorded through the experimental test of a prototype system. Collecting and utilizing battery data, especially fault data of each cell of a practical LIB pack, is one of the prime challenges while developing an ML-based fault detection/diagnosis system. Moreover, obtaining the fault data from the manufacturer is very difficult due to confidentiality and restriction on data access. The average training time, diagnosis time and total system running time of a particular ML-based strategy are seldomly reported in the existing literature. However, they should be mentioned so that researchers could get a reference for further research and development. This is highly desirable to obtain proper data through appropriate simulation study for developing ML-based models because simulating real physical faults in a laboratory is highly risky, costly and may be impractical. Regarding this, high-fidelity fault simulation tools are necessary, which further demands in-depth knowledge of battery fault behavior. Therefore, further study is recommended to obtain a clear understanding of the LIB fault behavior through extensive laboratory experiments with advanced equipment while maintaining proper safety measures. ML-based methods typically use external behaviors of the battery by recoding the commonly measured data such as voltage, current and temperature; however, these are often unable to provide sufficient information about the internal electrochemical dynamics of the battery. Different conditions could cause the same fault or even different faults may generate similar external characteristics. Most of the studies exclusively focused on a single LIB fault mechanism. Relationships among different fault mechanisms have not yet been established; thus, distinguishing faults accurately to generate appropriate control action is not possible with the existing techniques. Moreover, as ML-based techniques are highly dependent on the external parameters that are measured by sensors, isolating battery faults from sensor faults is a critical issue. That is why researchers have often assumed either the sensor or battery is trouble free, which may cause serious consequences in a real-life system. Therefore, further research on the fault identification methods is recommended besides improvement in fault detection strategies.

### *5.3. Current Issues and Research Scopes Related to Practicability and System Requirement*

The uncertainties during real-life application of LIBs including noise effect, different temperature conditions and cell aging were not considered during data acquisition in most of the existing studies. Thus, the effectiveness and accuracy of these diagnostic models while subjected to real-life situations need further evaluation. Detecting minor faults at an early stage is indeed a very difficult task; however, it could cause serious damage over a prolonged period. ML-based techniques have been unable to detect those early state faults so far. It not only demands very high quantity and high-resolution data but also requires a highly accurate, fast response, and precise sensors with high-end processors to accurately detect such faults. Thus, further research on sensing topology, processors and speedy data analysis is recommended here.

This review study noticed that the battery data used to formulate the ML-based strategies were recorded either through a simulation study or through an experimental test of a prototype system with a limited number of LIB cells. Installing one voltage and one temperature sensor per cell and one current sensor at each series string in prototype systems is feasible. However, installing sensors with each cell in a real-life LIB system with hundreds or even thousands of cells is impractical from a system size, cost and complexity point of view. While, at the same time, placing one voltage sensor in each parallel string and one current sensor in each series string reduces the observability and controllability of the system, resulting in inaccurate determination of fault location. Future research should focus on the diagnosis and detection methods with improved fault locating features with the minimum deployment of sensors or even sensorless strategies.

Despite high accuracy and efficiency, most of the data-driven ML-based fault diagnostic methods are unfit for practical application due to increasing stringent accuracy requirements. Most of the real-world applications of LIB pack such as EV, grid-tied power storage uses very high voltage and current level; thus, even a small inaccuracy may cause serious detrimental impacts on the system as well as on the users. The effectiveness of the proposed ML-based methods needs to be experimentally verified using the data of a real-life LIB system. Finally, the performance and accuracy of data-driven ML-based techniques are highly dependent on the programming complexity, quantity of data and processing power of the microcontroller. Advanced sophisticated battery-driven systems demand highly accurate and real-time fault detection and thereafter generating appropriate control action. Existing literature is unable to provide proper guidance regarding the selection of hardware. Therefore, further research and hardware development of fault diagnostic systems are recommended to minimize the reaction/approach time alongside the higher accommodating capacity of advanced ML algorithms and a large volume of data. Recently, a few studies have introduced the concept of cloud computing and parallel processing techniques to speed up the computation and learning processes of BMS. However, a cloud-based fault diagnosis method for LIB has not yet been developed. Cloud-based computing and integrated management of monitoring, diagnosis, prognosis and maintenance of LIB pack over the whole lifespan would be a future trend in the development of effective BMS for LIBs.

## 6. Conclusions

The fault detection/diagnosis in the lithium-ion battery (LIB) system has become a crucial task of the battery management system (BMS) with the increasing application of LIBs in highly sophisticated devices as well as high power applications. Realizing the promising future and several notable advantages of ML-based data-driven fault diagnosis techniques, a critical review of state-of-the-art ML-based fault diagnosis techniques is presented in this article. Special emphasis is given to the current issues and future challenges to provide a ready reference and guideline to researchers aiming to build a highly efficient, reliable, adaptive and easy to implement LIB fault diagnosis/detection strategy with better generalization capability.

In general, ML algorithms can be classified based on learning approaches, namely, supervised learning, unsupervised learning and reinforcement learning. Here, ML-based fault diagnosis models are categorized based on the type of ML approaches employed by the researchers. Overall, it is noticed that ML-based methods have been very recently adopted, and supervised learning-based approaches are mostly used. Among several other ML algorithms, Artificial Neural Network (ANN), Random Forest (RF) classifier, Support Vector Machine (SVM), Gaussian Process Regression (GPR) and Logistic Regression (LR) algorithms have been employed so far. It is also noticed that among these five approaches ANN-based techniques are most commonly used and considerable progress has been made by adopting advanced Neural Networks (NNs) and fusion with other algorithms such as Genetic Algorithm Back Propagation Neural Network (GA-BPNN) and Long Short-Term Memory Recurrent Neural Network (LSTM-RNN). The characteristics of LIB are highly

nonlinear and ANN-based methods showed the best results in capturing the nonlinearities. Despite high accuracy and adaptability to uncertainties the major limitations of ANN-based methods are the requirement of a large training data set, a large memory size, a time-consuming training process and poor generalization capability. SVM-based methods are the second most popular followed by ANN-based methods due to the lesser training data requirement, faster prediction and good performance in capturing the nonlinearities of LIB. Selecting a good kernel function and extensive quadratic programming are the major challenges. The remaining ML-based fault diagnosis methods have been very recently adopted. Despite their impressive performance in a laboratory test using a prototype system, it is too early to judge their performance in a real-world system. Significant further research and development are recommended before practical application. Overall, ML-based strategies are also very effective in capturing the nonlinearities of LIB, are highly efficient and are accurate in fault diagnosis. However, the requirement of high volume and quality of training data, especially battery fault data, algorithmic complexity, computational time, and large memory requirement, are some of the common limitations of the current strategies.

Apart from the specific issues and challenges of ML-based techniques, there are several other general issues and challenges of LIB fault diagnosis. Some of these include: The adoptive fault threshold selection, assumption-free fault isolation, absence of fault simulation tools, limitation of hardware and early fault detection. The development of a fault-diagnosis scheme adaptive to cell aging, cell inconsistencies, measurement noises and the uncertainties of real-life applications is also a vital challenge. Moreover, the battery fault mechanisms and characteristics of all kinds of faults in LIB are still not fully understood. Owing to the inherent limitation of a single fault diagnosis method, a promising trend is to combine multiple fault features and multiple diagnostic methods aiming to improve accuracy and robustness. It could be stated as a concluding remark that ML-based fault diagnostics of LIBs are still at their early stage. However, with the continuous enrichment of the ML theory and the development of low-cost powerful microcontrollers alongside the increasing availability of battery data in the era of big data, and highly advanced testing equipment, ML-based fault diagnostic methods will inevitably become the next generation of intelligent battery fault detection/diagnosis strategies.

**Author Contributions:** Conceptualization, A.S. and S.S.W.; methodology, S.C. and S.S.W.; investigation, A.S.; resources, S.S.W.; writing—original draft preparation, A.S.; writing—review and editing, S.C. and S.S.W.; visualization, A.S.; supervision, S.C. and S.S.W. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Luo, X.; Kang, L.; Lu, C.; Linghu, J.; Lin, H.; Hu, B. An Enhanced Multicell-to-Multicell Battery Equalizer Based on Bipolar-Resonant LC Converter. *Electronics* **2021**, *10*, 293. [[CrossRef](#)]
2. Gao, M.; Qu, J.; Lan, H.; Wu, Q.; Lin, H.; Dong, Z.; Zhang, W. An active and passive hybrid battery equalization strategy used in group and between groups. *Electronics* **2020**, *9*, 1744. [[CrossRef](#)]
3. Xing, Y.; Ma, E.W.M.; Tsui, K.L.; Pecht, M. Battery management systems in electric and hybrid vehicles. *Energies* **2011**, *4*, 1840–1857. [[CrossRef](#)]
4. Gabbar, H.A.; Othman, A.M.; Abdussami, M.R. Review of Battery Management Systems (BMS) Development and Industrial Standards. *Technologies* **2021**, *9*, 28. [[CrossRef](#)]
5. Doridant, A.; Abouda, K.; Givelin, P.; Thibaud, B. Battery Management System Demonstrator Board design using EMC System simulation. In Proceedings of the EMC Europe 2019—2019 International Symposium on Electromagnetic Compatibility, Barcelona, Spain, 2–6 September 2019.
6. Aiello, O.; Crovetto, P.S.; Fiori, F. Susceptibility to EMI of a Battery Management System IC for electric vehicles. In Proceedings of the IEEE International Symposium on Electromagnetic Compatibility, Dresden, Germany, 16–22 August 2015.
7. Aiello, O. Electromagnetic susceptibility of battery management systems' ICs for electric vehicles: Experimental study. *Electronics* **2020**, *9*, 510. [[CrossRef](#)]

8. Jaguemont, J.; Boulon, L.; Dubé, Y. A comprehensive review of lithium-ion batteries used in hybrid and electric vehicles at cold temperatures. *Appl. Energy* **2016**, *164*, 99–114. [[CrossRef](#)]
9. Lee, C.-J.; Kim, B.-K.; Kwon, M.-K.; Nam, K.; Kang, S.-W. Real-Time Prediction of Capacity Fade and Remaining Useful Life of Lithium-Ion Batteries Based on Charge/Discharge Characteristics. *Electronics* **2021**, *10*, 846. [[CrossRef](#)]
10. Lelie, M.; Braun, T.; Knips, M.; Nordmann, H.; Ringbeck, F.; Zappen, H.; Sauer, D.U. Battery management system hardware concepts: An overview. *Appl. Sci.* **2018**, *8*, 534. [[CrossRef](#)]
11. Ko, Y.; Choi, W. A new soc estimation for lfp batteries: Application in a 10 ah cell (hw 38120 l/s) as a hysteresis case study. *Electronics* **2021**, *10*, 705. [[CrossRef](#)]
12. Xu, P.; Li, J.; Sun, C.; Yang, G.; Sun, F. Adaptive state-of-charge estimation for lithium-ion batteries by considering capacity degradation. *Electronics* **2021**, *10*, 122. [[CrossRef](#)]
13. Sung, W.; Lee, J. Implementation of SOH estimator in automotive BMSs using recursive least-squares. *Electronics* **2019**, *8*, 1237. [[CrossRef](#)]
14. Jiang, Y.; Jiang, J.; Zhang, C.; Zhang, W.; Gao, Y.; Li, N. State of health estimation of second-life LiFePO<sub>4</sub> batteries for energy storage applications. *J. Clean. Prod.* **2018**. [[CrossRef](#)]
15. Surya, S.; Marcis, V.; Williamson, S. Core Temperature Estimation for a Lithium ion 18650 Cell. *Energies* **2020**, *14*, 87. [[CrossRef](#)]
16. Samanta, A.; Chowdhuri, S. Active Cell Balancing of Lithium-ion Battery Pack Using Dual DC-DC Converter and Auxiliary Lead-acid Battery. *J. Energy Storage* **2020**, 102109. [[CrossRef](#)]
17. Uno, M.; Ueno, T.; Yoshino, K. Cell voltage equalizer using a selective voltage multiplier with a reduced selection switch count for series-connected energy storage cells. *Electronics* **2019**, *8*, 1303. [[CrossRef](#)]
18. Xiong, R.; Yu, Q.; Shen, W. Review on sensors fault diagnosis and fault-tolerant techniques for lithium ion batteries in electric vehicles. In Proceedings of the 13th IEEE Conference on Industrial Electronics and Applications, ICIEA 2018, Wuhan, China, 31 May–2 June 2018.
19. Tran, M.K.; Fowler, M. A review of lithium-ion battery fault diagnostic algorithms: Current progress and future challenges. *Algorithms* **2020**, *13*, 62. [[CrossRef](#)]
20. Abada, S.; Marlair, G.; Lecocq, A.; Petit, M.; Sauvart-Moynot, V.; Huet, F. Safety focused modeling of lithium-ion batteries: A review. *J. Power Sources* **2016**, *306*, 178–192. [[CrossRef](#)]
21. Wang, Z.; Hong, J.; Liu, P.; Zhang, L. Voltage fault diagnosis and prognosis of battery systems based on entropy and Z-score for electric vehicles. *Appl. Energy* **2017**. [[CrossRef](#)]
22. Wu, C.; Zhu, C.; Ge, Y. A New Fault Diagnosis and Prognosis Technology for High-Power Lithium-Ion Battery. *IEEE Trans. Plasma Sci.* **2017**, *45*, 1533–1538. [[CrossRef](#)]
23. Kim, H.; Shin, K.G. Modeling of externally-induced/common-cause faults in fault-tolerant systems. In Proceedings of the IEEE/AIAA Digital Avionics Systems Conference, Phoenix, AZ, USA, 30 October–3 November 1994.
24. Wu, C.; Zhu, C.; Ge, Y.; Zhao, Y. A Review on Fault Mechanism and Diagnosis Approach for Li-Ion Batteries. *J. Nanomater.* **2015**. [[CrossRef](#)]
25. Smarsly, K.; Law, K.H. Decentralized fault detection and isolation in wireless structural health monitoring systems using analytical redundancy. *Adv. Eng. Softw.* **2014**. [[CrossRef](#)]
26. Williard, N.; He, W.; Hendricks, C.; Pecht, M. Lessons learned from the 787 dreamliner issue on Lithium-Ion Battery reliability. *Energies* **2013**, *6*, 4682–4695. [[CrossRef](#)]
27. Hu, X.; Zhang, K.; Liu, K.; Lin, X.; Dey, S.; Onori, S. Advanced Fault Diagnosis for Lithium-Ion Battery Systems. *TechRxiv* **2020**. [[CrossRef](#)]
28. Lu, L.; Han, X.; Li, J.; Hua, J.; Ouyang, M. A review on the key issues for lithium-ion battery management in electric vehicles. *J. Power Sources* **2013**, *226*, 272–288. [[CrossRef](#)]
29. Lyu, D.; Ren, B.; Li, S. Failure modes and mechanisms for rechargeable Lithium-based batteries: A state-of-the-art review. *Acta Mech.* **2019**, *230*, 701–727. [[CrossRef](#)]
30. Hu, X.; Zhang, K.; Liu, K.; Lin, X.; Dey, S.; Onori, S. Advanced Fault Diagnosis for Lithium-Ion Battery Systems: A Review of Fault Mechanisms, Fault Features, and Diagnosis Procedures. *IEEE Ind. Electron. Mag.* **2020**, *14*, 65–91. [[CrossRef](#)]
31. Ubar, R.; Kostin, S.; Raik, J. Synthesis of multiple fault oriented test groups from single fault test sets. In Proceedings of the 2013 8th International Conference on Design and Technology of Integrated Systems in Nanoscale Era (DTIS), Abu Dhabi, United Arab Emirates, 26–28 March 2013.
32. Ubar, R.; Devadze, S.; Raik, J.; Jutman, A. Parallel X-fault simulation with critical path tracing technique. In Proceedings of the Design, Automation and Test in Europe, Dresden, Germany, 8–12 March 2010.
33. Ubar, R.-J. Hierarchical Test Generation Based on an Alternative Graph Model. Master’s Thesis, Tallinn Technical University, Tallinn, Estonia, April 1997.
34. Ardeshiri, R.R.; Balagopal, B.; Alsabbagh, A.; Ma, C.; Chow, M.Y. Machine Learning Approaches in Battery Management Systems: State of the Art: Remaining useful life and fault detection. In Proceedings of the 2020 2nd IEEE International Conference on Industrial Electronics for Sustainable Energy Systems, IESES 2020, Cagliari, Italy, 1–3 September 2020.
35. Varshney, A.; Ghosh, S.K.; Padhy, S.; Tripathy, R.K.; Acharya, U.R. Automated Classification of Mental Arithmetic Tasks Using Recurrent Neural Network and Entropy Features Obtained from Multi-Channel EEG Signals. *Electronics* **2021**, *10*, 1079. [[CrossRef](#)]

36. Lain, J.-K.; Chen, Y.-H. An ANN-Based Adaptive Predistorter for LED Nonlinearity in Indoor Visible Light Communications. *Electronics* **2021**, *10*, 948. [\[CrossRef\]](#)
37. Walczak, S. Artificial neural networks. In *Advanced Methodologies and Technologies in Artificial Intelligence, Computer Simulation, and Human-Computer Interaction*; Khosrow-Pour, D.B.A.M., Ed.; Advances in Computer and Electrical Engineering; IGI Global: Hershey, PA, USA, 2019; pp. 40–53. ISBN 9781522573685.
38. Memar, P.; Faradji, F. A Novel Multi-Class EEG-Based Sleep Stage Classification System. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2018**. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Wang, Z.; Zhang, Q.; Xiong, J.; Xiao, M.; Sun, G.; He, J. Fault Diagnosis of a Rolling Bearing Using Wavelet Packet Denoising and Random Forests. *IEEE Sens. J.* **2017**. [\[CrossRef\]](#)
40. Abd El Meguid, M.K.; Levine, M.D. Fully automated recognition of spontaneous facial expressions in videos using random forest classifiers. *IEEE Trans. Affect. Comput.* **2014**. [\[CrossRef\]](#)
41. Zhang, H.; Li, Q.; Liu, J.; Shang, J.; Du, X.; McNairn, H.; Champagne, C.; Dong, T.; Liu, M. Image Classification Using RapidEye Data: Integration of Spectral and Textual Features in a Random Forest Classifier. *IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens.* **2017**. [\[CrossRef\]](#)
42. Zhao, B.; Cao, Z.; Wang, S. Lung vessel segmentation based on random forests. *Electron. Lett.* **2017**. [\[CrossRef\]](#)
43. Choi, D.; Yim, J.; Baek, M.; Lee, S. Machine learning-based vehicle trajectory prediction using v2v communications and on-board sensors. *Electronics* **2021**, *10*, 420. [\[CrossRef\]](#)
44. Xie, S.; Du, S.; Lv, J.; Deng, Y.; Jia, S. A hybrid prognostics deep learning model for remaining useful life prediction. *Electronics* **2021**, *10*, 39. [\[CrossRef\]](#)
45. Dietterich, T.G. Ensemble Methods in Machine Learning. In *International Workshop on Multiple Classifier Systems*; Springer: Berlin/Heidelberg, Germany, 2000; pp. 1–15.
46. Yin, Z.; Wang, L.; Zhang, Y.; Gao, Y. A novel arc fault detection method integrated random forest, improved multi-scale permutation entropy and wavelet packet transform. *Electronics* **2019**, *8*, 396. [\[CrossRef\]](#)
47. Kim, B.; Im, S.; Yoo, G. Performance evaluation of cnn-based end-point detection using in-situ plasma etching data. *Electronics* **2021**, *10*, 49. [\[CrossRef\]](#)
48. Ma, Y.; Guo, G. *Support Vector Machines Applications*; Springer International Publishing: Cham, Switzerland, 2014; ISBN 9783319023007.
49. Wang, S.H.; Zhan, T.M.; Chen, Y.; Zhang, Y.; Yang, M.; Lu, H.M.; Wang, H.N.; Liu, B.; Phillips, P. Multiple Sclerosis Detection Based on Biorthogonal Wavelet Transform, RBF Kernel Principal Component Analysis, and Logistic Regression. *IEEE Access* **2016**. [\[CrossRef\]](#)
50. Dong, L.; Wesseloo, J.; Potvin, Y.; Li, X. Discrimination of Mine Seismic Events and Blasts Using the Fisher Classifier, Naive Bayesian Classifier and Logistic Regression. *Rock Mech. Rock Eng.* **2016**. [\[CrossRef\]](#)
51. Ortiz, J.P.; Valladolid, J.D.; Garcia, C.L.; Novillo, G.; Berrezueta, F. Analysis of machine learning techniques for the intelligent diagnosis of Ni-MH battery cells. In Proceedings of the 2018 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC), Ixtapa, Mexico, 14–16 November 2018; pp. 1–6. [\[CrossRef\]](#)
52. Gao, Z.; Chin, C.S.; Woo, W.L.; Jia, J.; Toh, W.D. Genetic Algorithm based Back-Propagation Neural Network approach for fault diagnosis in lithium-ion battery system. In Proceedings of the 2015 6th International Conference on Power Electronics Systems and Applications (PESA), Hong Kong, China, 15–17 December 2016. [\[CrossRef\]](#)
53. Sbarufatti, C.; Corbetta, M.; Giglio, M.; Cadini, F. Adaptive prognosis of lithium-ion batteries based on the combination of particle filters and radial basis function neural networks. *J. Power Sources* **2017**, *344*, 128–140. [\[CrossRef\]](#)
54. Zhao, Y.; Liu, P.; Wang, Z.; Zhang, L.; Hong, J. Fault and defect diagnosis of battery for electric vehicles based on big data analysis methods. *Appl. Energy* **2017**, *207*, 354–362. [\[CrossRef\]](#)
55. Gao, Z.; Chin, C.S.; Chiew, J.H.K.; Jia, J.; Zhang, C. Design and implementation of a smart lithium-ion battery system with real-time fault diagnosis capability for electric vehicles. *Energies* **2017**, *10*, 15–18. [\[CrossRef\]](#)
56. Hong, J.; Wang, Z.; Yao, Y. Fault prognosis of battery system based on accurate voltage abnormality prognosis using long short-term memory neural networks. *Appl. Energy* **2019**, *251*, 113381. [\[CrossRef\]](#)
57. Yang, R.; Xiong, R.; He, H.; Chen, Z. A fractional-order model-based battery external short circuit fault diagnosis approach for all-climate electric vehicles application. *J. Clean. Prod.* **2018**, *187*, 950–959. [\[CrossRef\]](#)
58. Naha, A.; Khandelwal, A.; Agarwal, S.; Tagade, P.; Hariharan, K.S.; Kaushik, A.; Yadu, A.; Kolake, S.M.; Han, S.; Oh, B. Internal short circuit detection in Li-ion batteries using supervised machine learning. *Sci. Rep.* **2020**, *10*, 1–10. [\[CrossRef\]](#)
59. Yao, L.; Fang, Z.; Xiao, Y.; Hou, J.; Fu, Z. An Intelligent Fault Diagnosis Method for Lithium Battery Systems Based on Grid Search Support Vector Machine. *Energy* **2021**, *214*, 118866. [\[CrossRef\]](#)
60. Hashemi, S.R.; Bahadoran Baghbadorani, A.; Esmaeli, R.; Mahajan, A.; Farhad, S. Machine learning-based model for lithium-ion batteries in BMS of electric/hybrid electric aircraft. *Int. J. Energy Res.* **2021**, *45*, 5747–5765. [\[CrossRef\]](#)
61. Liu, D.; Zhou, J.; Pan, D.; Peng, Y.; Peng, X. Lithium-ion battery remaining useful life estimation with an optimized Relevance Vector Machine algorithm with incremental learning. *Meas. J. Int. Meas. Confed.* **2015**. [\[CrossRef\]](#)
62. Jia, S.; Ma, B.; Guo, W.; Li, Z.S. A sample entropy based prognostics method for lithium-ion batteries using relevance vector machine. *J. Manuf. Syst.* **2021**. [\[CrossRef\]](#)

63. Zhao, L.; Wang, Y.; Cheng, J. A hybrid method for remaining useful life estimation of lithium-ion battery with regeneration phenomena. *Appl. Sci.* **2019**, *9*, 1890. [[CrossRef](#)]
64. Tagade, P.; Hariharan, K.S.; Ramachandran, S.; Khandelwal, A.; Naha, A.; Kolake, S.M.; Han, S.H. Deep Gaussian process regression for lithium-ion battery health prognosis and degradation mode diagnosis. *J. Power Sources* **2020**, *445*, 227281. [[CrossRef](#)]
65. Zhang, Y.; Tang, Q.; Zhang, Y.; Wang, J.; Stimming, U.; Lee, A.A. Identifying degradation patterns of lithium ion batteries from impedance spectroscopy using machine learning. *Nat. Commun.* **2020**, *11*, 6–11. [[CrossRef](#)]
66. Rush, B.; Celi, L.A.; Stone, D.J. Applying machine learning to continuously monitored physiological data. *J. Clin. Monit. Comput.* **2019**, *33*, 887–893. [[CrossRef](#)] [[PubMed](#)]
67. McDonald, A.D.; Sasangohar, F.; Jatav, A.; Rao, A.H. Continuous monitoring and detection of post-traumatic stress disorder (PTSD) triggers among veterans: A supervised machine learning approach. *IJSE Trans. Healthc. Syst. Eng.* **2019**, *9*, 201–211. [[CrossRef](#)]