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Review article

EV battery fault diagnostics and prognostics using deep learning: Review, challenges & opportunities

Ram Machlev

General Motors Technical Center Israel, 13 Arie Shenkar St., Herzliya 4672513, Israel

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ABSTRACT

The widespread growth of electric vehicles (EV)s has highlighted the need for effective diagnostic and prognostic techniques for EV battery faults. Lately, deep learning (DL) techniques are being adopted for battery faults detection, diagnostics and prognostics and their potential is still not yet fully covered for these tasks. In this light, it is the purpose of this paper to highlight the potential of using DL for EV battery fault diagnostics and prognostics. We first provide background on familiar battery faults. Then, we present state-of-the-art DL techniques for detecting the battery faults. Later, we review and analyze the recent work on this topic, and the on-going trends in the research community. Finally, we present the challenges of using DL in such applications and suggest opportunities and future research directions which will allow to improve the fault detection mechanism. We hope that this paper will trigger fruitful discussions and encourage further research on this important emerging topic.

1. Introduction

Over the past few years energy storage technologies have been slowly emerging as an essential component of modern power systems [1]. Particularly, batteries, mainly lithium-ion batteries (LIB), are being used in electric vehicles (EV) [2]. It is assumed that EV sales will increase significantly in the coming years, and by 2035 the EV market share is expected to reach 42.5% worldwide [3]. Currently, the reputation of LIBs was damaged after events in which explosions and fires accident occurred due to different failures [4]. Therefore, safety technologies for LIBs operation are becoming a necessity and are developed continuously [5,6].

Due to this challenge, in the last couple of years new techniques and principles are being developed to improve the diagnostics and prognostics of EV battery faults. Battery fault diagnosis and prognostics techniques are essential for ensuring the safety of EVs. EVs rely on complex electrical systems, and any faults or malfunctions in these systems can pose significant safety risks to both the vehicle occupants and the surrounding environment. By implementing these techniques, potential issues or abnormalities can be detected and identified early on. This allows for timely repairs or maintenance to prevent further damage or potential hazards. These techniques involve mainly monitoring and analyzing various parameters and signals from the BMS in order to identify any deviations from normal operation. Also, some of these methods focus on predicting the future behavior of the battery. This is crucial for EVs as the battery is a key component that directly impacts the vehicle's performance and range. By accurately estimating the behavior of the battery, EV owners and operators can plan for battery replacements or take necessary precautions to avoid unexpected failures.

Accordingly, many reviews were published in the literature, summarizing different research in this field. For example, [7] focus on the diagnosis and prognosis of short circuit, covering the method and the key indicators. In [8] a comprehensive survey of condition monitoring and fault diagnosis strategies for electric vehicle major components and subsystems is provided. One of the EV components that are discussed in this review is the battery, its potential faults and detection techniques. Also, in reviews [9–11] methods adopted in fault diagnosis of battery system are classified and discussed. The suggested algorithms that are used for LIB fault diagnostics can be divided into two groups: model-based methods and non-model based methods. The second group contains also algorithms of machine learning (ML) and artificial intelligence (AI) which starts to become more common lately. For example, in [12,13] ML techniques in LIB degradation research are reviewed.

Meanwhile, with the evolution of deep learning (DL), better classifiers and algorithms are being developed for energy applications [14,15] which outperform traditional classification and detection algorithms. Two examples in the LIB domain are [16,17] which explore various DL approaches for battery state estimation, thermal management and prediction. Additionally, DL for battery fault diagnostics in EV is being used more often in last couple of years.

E-mail address: ram.machlev@gm.com.

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List of abbreviations

AI	Artificial Intelligence
BMS	Battery Management System
CNN	Convolutional Neural Network
DL	Deep Learning
DNN	Deep Neural Networks
ECM	Equivalent Circuit Model
ESC	External Short Circuit
EV	Electric Behicle
FNN	Feedforward Neural Network
ISC	Internal Short Circuit
LIB	Lithium-ion Batteries
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MSE	Mean Squared Error
NARAX	nonlinear AutoRegressive eXogenous
NAS	Neural Architecture Search
NBAOLN	National Bigdata Alliance Open Laboratory of NEVs
NMMC	National Monitoring and Management Center
NN	Neural Networks
PINN	Physics-Informed Neural Networks
ReLU	Rectified Linear Unit
RMSE	Root Mean Squared Error
SC	Short Circuit
SEI	Solid Electrolyte Interphase
SMC	Service and Management Center
SOC	State of Charge
SOH	State of health
TR	Thermal Runaway
TRP	Thermal Runaway Propagation
XAI	eXplainable Artificial Intelligence

In this light, the purpose of this work is to highlight the potential of using DL in the context of EV battery fault diagnostics and prognostics. We first present technical background regarding battery faults and DL techniques. Then, we review and analyze the recent work on this topic, and the on-going trends in the research community. Finally, we present challenges and opportunities of using DL for battery faults, and suggest several directions for future research, that may assist in coping with the mentioned challenges. The specific contributions of this paper are the as follows:

1. A short survey of work related to the use of DL for EV battery fault diagnostics and prognostics is presented. We attempt to better understand which DL techniques are the most common and why, and also why specific methods are used for specific faults.
2. The main challenges of adopting and implementing DL techniques for EV battery faults are presented.
3. Potential opportunities and future research directions related to DL and EV battery faults are provided.

The rest of the paper is organized as follows. Section 2 provides background on battery faults and technical background on DL and evaluation metrics. Section 3 presents literature review of DL for battery faults in EV. Section 4 discusses trends, potential challenges, opportunities and future research directions of DL for battery faults in EV. Finally, Section 5 concludes the paper.

2. Technical background

2.1. Battery faults in EV

Numerous studies have been conducted to investigate LIBs, as documented in the literature [6,18]. In this section, we will provide a concise overview of the prevalent faults. Specifically, we have classified EV battery faults into four main groups: battery management system (BMS), battery pack, charging, and short circuit issues.

The first category pertains to the Battery Management System (BMS), which is a crucial component responsible for monitoring and managing battery health and safety [19]. BMS-related problems can arise due to several reasons, such as communication issues [20], which may be triggered by electromagnetic interference or wire disconnections caused by vibrations [21]. Another factor contributing to BMS issues is sensor faults. The most critical sensor measurements include cells voltage, module current, and module temperature. Sensor faults can appear as value bias, value drift, frozen values, delays, and can be caused by inherent defects, aging, and other factors [22].

The second category pertains to battery pack failures. One specific fault is related to the thermal management system, which can arise from coolant and relay failures, potentially resulting in overheating within the battery pack [23]. Another fault involves issues with the contactor, which can lead to problems in cutting off the high-voltage circuit [24]. Contactors can develop faults due to erosion caused by high temperatures. Additionally, insulation problems can occur when the insulation layer is damaged, and high-voltage wiring adhesion takes place, allowing external liquid to enter the battery pack and causing abnormal decrease in total power and energy [25]. Another potential fault is cell connection, where adjacent cells are not adequately connected due to bolt looseness or vibration [26], leading to a reduction in overall power and energy. Moreover, inconsistencies in battery parameters can be considered as faults, resulting from manufacturing variations or different operating conditions [27,28].

Another category concerns charging issues. Overcharge and overdischarge can give rise to various faults [29,30]. These faults can significantly reduce the lifespan and thermal stability of the cells, leading to swelling. Charging faults can occur due to multiple reasons, including incorrect voltage and current measurements, inaccurate estimation state of charge (SOC), cell capacity variations, and high charging rates towards the end of the charging process. Overcharging can occur when there is a fault in the charger or when the charger malfunctions and continues to supply excessive charge. Overcharged lithium-ion batteries undergo electrochemical reactions, resulting in the loss of active materials. Furthermore, overcharging leads to the formation of a thick solid electrolyte lithium plating, which drastically reduces battery life and limits fast-charging capabilities. In the case of overdischarge, the battery continues to discharge even after reaching the discharge cut-off voltage. Overdischarging can have detrimental effects such as capacity loss and corrosion of current collectors due to significant changes occurring at the anode.

The final category is short circuit (SC) faults, which can be further divided into external short circuit (ESC) and internal short circuit (ISC) [7,31]. ESC refers to a situation where there is a path of low resistance between the tabs [32]. This occurrence often arises from overcharging, which results in swollen cells and subsequent electrolyte leakage. It can also happen due to water immersion or the presence of heat elements that fuse the terminals together. On the other hand, ISC occurs when the insulating separator layer between the electrodes fails [33]. This failure can be attributed to factors such as high temperature, cell deformation, and dendrite growth, which can lead to separator tearing, piercing, or collapsing. Damage to the separator allows for the penetration of electrons and ions through the separator layer, enabling their movement across the electrolyte. Another class of ISCs are chemical shorts: lithium dendrites formed on some

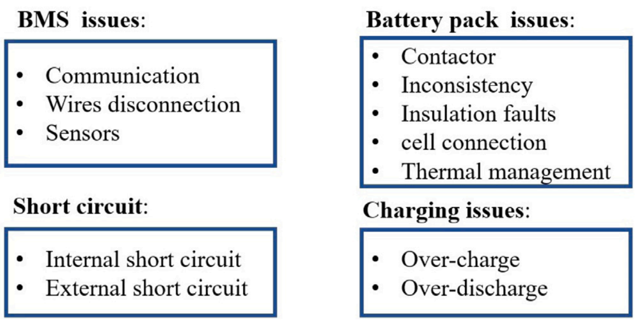

Fig. 1. Possible EV battery faults. The faults are divided into four groups- BMS, Battery pack, short circuit and charging issues. Some of these faults may eventually lead to thermal runaway, specifically internal short circuit and charging issues.

charging and copper dendrites by over-discharging ISC is a significant contributor to thermal runaway.

Thermal runaway (TR), as defined in [34], refers to a phenomenon where mechanical, electrical, or thermal abuse results in a critical temperature increase. This temperature level is typically the melting point of metallic lithium and can lead to a reaction that causes fire and explosions. Various factors can contribute to the occurrence of TR, such as

- Internal short circuit- when a short circuit occurs within the battery, it can cause a rapid increase in current flow, leading to excessive heat generation.
- Overcharging- can cause the accumulation of excessive energy, leading to increased heat generation.
- External damage- physical damage to the battery, such as crush, punctures or impacts, can compromise the integrity of the battery's internal components. This damage can lead to internal short circuits or other faults that may trigger thermal runaway.
- Manufacturing defects- faulty manufacturing processes or materials can lead to internal defects within the battery, such as dendrites or metal particles. These defects can cause internal short circuits and increase the risk of thermal runaway.

Note that certain battery faults may not directly lead to thermal runaway but can still impact the performance and safety of the battery.

When heat transfers to neighboring cells, it leads to thermal propagation, also known as thermal runaway propagation (TRP). With an increasing number of cells, the probability of TRP also increases. TRP is considered the most undesirable and severe fault due to the high risk it poses to passengers and the environment. To mitigate TRP, numerous techniques are being used and developed in both industry and academia [34]. These include data-driven approaches that have recently been suggested [35–38]. Fig. 1 summarizes the discussed EV battery faults.

It is worth noting that numerous studies are dedicated to investigating voltage abnormalities in batteries. Voltage abnormality can manifest in various forms, including over-voltage, under-voltage, transients, and others. These abnormalities have the potential to cause several battery faults, such as overcharging, overdischarging, wire connection problems, poor consistency, internal short circuits, and more. The impact of voltage abnormalities on battery performance and safety is a significant area of research in the field.

2.2. Deep learning: Motivation and technical background

2.2.1. Motivation

While various machine learning methods have been used for electric vehicle fault diagnosis over the past century, none have been able to completely solve the challenge of detecting thermal runaway propagation (TRP) or other faults before they happen. However, deep learning (DL) shows great promise in addressing this issue in the coming decade as it represents the current state-of-the-art technology in many fields. Deep learning offers several compelling reasons for its application in electric vehicle battery fault diagnosis and is considered the future direction for development in this field. Here are some key advantages and reasons for choosing deep learning:

- In the context of battery fault diagnosis, deep learning algorithms can effectively analyze complex data patterns and identify subtle indicators of potential faults, enabling early detection and prevention.
- DL classifiers can learn directly from raw data, eliminating the need for manual feature engineering. This end-to-end learning approach allows deep learning algorithms to automatically extract relevant features from the input data, making them highly adaptable and capable of handling diverse and evolving battery fault scenarios.
- DL models can scale to handle large datasets and can be trained on a wide range of battery types and fault scenarios. This scalability and adaptability make deep learning suitable for real-world applications, where battery systems and fault patterns can vary significantly. It is worth noting that, to the best of our knowledge, there is a lack of research that specifically addresses multiple types of faults. Most existing works in this field classify the output as either normal or a specific fault that the model has been trained for. Only a few studies have focused on more than one type of fault, and typically no more than three. These studies use DL approach, mainly.
- DL algorithms have demonstrated superior performance in various domains, including image and speech recognition. By leveraging deep neural networks, electric vehicle battery fault detection can achieve higher accuracy rates compared to traditional methods.

Considering these advantages, DL offers unparalleled potential and irreplaceability in the field of electric vehicle battery fault diagnosis, making it a compelling choice for future development and research.

2.2.2. Technical background

Deep learning is a subgroup of machine learning methods, which is based on artificial neural networks (ANN)s. In general, ANNs are inspired by the structure of the brain's neural networks, mimicking their learning capability from experience. Essentially, when a neural network is trained using past data, it can generate outputs based on the knowledge extracted from the training process. During the training phase, the training data, or features, are fed into the input layer of the neural network. The weights between the nodes in the network are adjusted iteratively to improve the network performance on the given task. After the weights are updated, the network can effectively map inputs to their corresponding outputs. Machine learning and deep learning techniques can be broadly classified into three categories: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning the mathematical model is designed to best predict the relations between given inputs $X = [x_1, x_2, \dots, x_n]$ and ground truth outputs $Y[y_1, y_2, \dots, y_n]$. The main goal is to estimate a function $f(x)$, which constitutes a mapping from x to y, such that the expected value of a specific cost function $L(f(x), y)$ is minimized. In unsupervised learning methods the output data is unavailable, and the objective is to find patterns in the input data. The third category, reinforcement learning, is not commonly used for EV battery faults and will not be discussed in this work. In this subsection we will present common DL architectures.

2.2.3. Feedforward neural network

Feedforward Neural Network (FNN) is a classic artificial neural network which its basic architecture is illustrated in Fig. 2 [39]. For

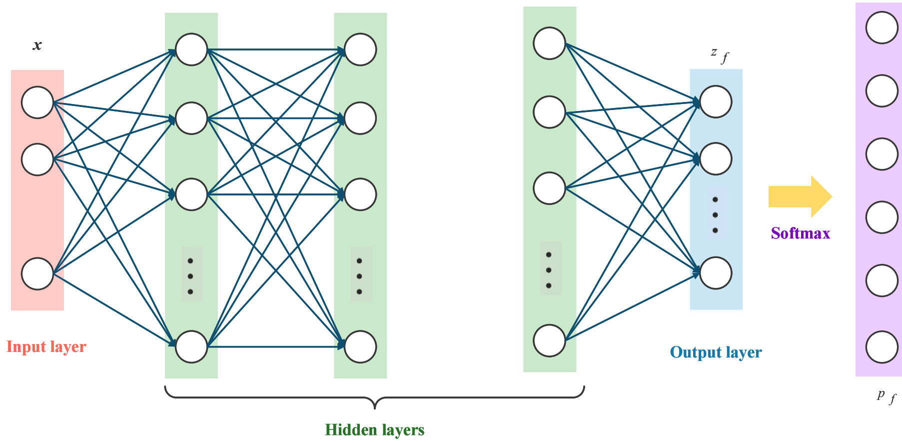

Fig. 2. Illustration of FNN structure.

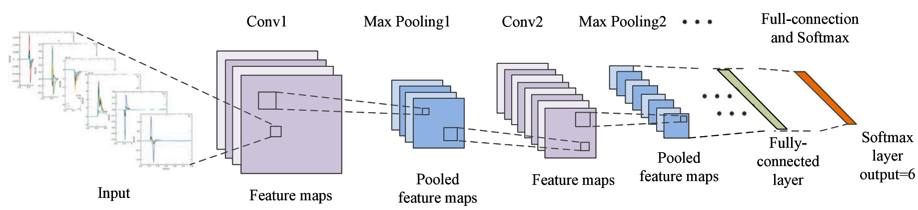

Fig. 3. Illustration of CNN structure.

FNN model, the data flows forward through an input layer, one or more hidden layers, and an output layer. Notice that the input layer should have as many neurons as the dimension of the input data. Between two adjacent layers, an activation function is adopted to receive the output signal from the previous layer and convert them into the next layer's input. Two of the most commonly activation functions used are sigmoid and hyperbolic tangent, which are, respectively, expressed as follows

$$a_{\text{sigmoid}}(x) = \frac{1}{1+e^{x}}, \tag{1}$$

and

$$a_{\tanh}(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}. \tag{2}$$

These activation functions, which area monotonically increasing, continuous functions, are applied to the weighted input of a neuron to produce its output. Since most of the classification tasks are multi-class classification problems, the activation function of output layer in FNN is a softmax function. It creates a probability distribution to determine which class the input sample belongs to. The neuron with the highest probability denotes the predicted label. For a vector x with m elements, the softmax function is calculated by

$$a_{\text{softmax}}(x) = = \frac{e^{x_i}}{\sum_{i=1}^{m} e^{x_i}}. \tag{3}$$

The NN is trained by minimizing the differences between the processed output generated by the network and the actual target output. For each training sample in the training set, the feature vector is presented as input to the neural network. The network then generates a predicted output, which is compared with the corresponding known label or target output. The difference between the predicted output and the target output is measured using a cost function, which quantifies the dissimilarity between the predicted and target outputs.

2.2.4. Convolutional neural network

A common deep learning model used for classification is the Convolutional Neural Network (CNN) [40,41]. A CNN consists of an input layer, one or more convolutions and activation layers, and an output layer. Mathematically, the convolutional layer is modeled as

$$Z = X \otimes F, \tag{4}$$

where X is the input, F is the filter, and Z is the output. Commonly, Z is activated with a non-linear layer, which allows the CNN to approximate arbitrary functions. One common non-linear layer used is the Rectified Linear Unit (ReLU) which is defined mathematically as

$$a_{\text{ReLU}}(Z) = \max(0, Z), \tag{5}$$

where Z is the output of the previous convolutional layer. The basic structure of the CNN is shown in Fig. 3. The convolution operation helps the CNN enlarge features of image to progressively larger areas of the input. This extraction of features takes advantage of the strong correlation among neighboring pixels. In a CNN, convolution layers employ filters to create feature maps and a max-pooling layers are used to reshape and condense the obtained feature maps. In Fig. 3, a fully connected layer and a softmax layer are added as the output layer. The cross-entropy is the cost function that typically used in the training process.

2.2.5. Long short term memory

Long short term memory (LSTM) is a recurrent neural network [42,43], meaning that there are feedback connections within the network as opposed to only feed-forward connections between layers in FNNs. This feedback allows for better handling of sequential data, such as sentences, video streams and any time series signal. LSTM is a robust deep learning model demonstrating excellent performance and efficiency compared to traditional neural networks on sequence data [44,45]. LSTM architecture is special since it can decide the importance of previous information in short-term memory and thus longer dependencies in sequences can recognized. This concept helps dealing with the vanishing gradient problems, by allowing gradients to pass through the cell without modifying the value. Mathematically we define the input as x_t, the previous cell state (long-term memory of the model) as c_{t-1}, and the previous state of hidden state (short-term memory of the model)

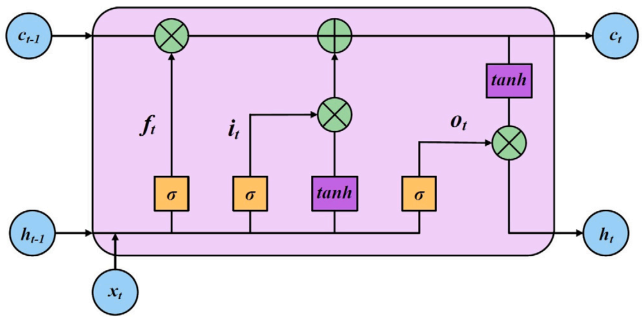

Fig. 4. Illustration of LSTM cell.

as h_{t-1} which can be shown in Fig. 4. The forget gate decides which information from previous and current states is saved and is defined as

$$f_t = a_{\text{sigmoid}}(W_{xf} x_t + W_{hf} h_{t-1} + b_z) \tag{6}$$

where W_{xz} and W_{hz} are network weights, h_{t-1} is the previous state, b_z is a bias term, and a_{sigmoid} is a sigmoid function. The input gate decides how valuable the current input is and defined as

$$i_t = a_{\text{sigmoid}}(W_{xi} x_t + W_{hi} h_{t-1} + b_i), \tag{7}$$

which later combined to cell state C_t as follows

$$C_t = f_t \times C_{t-1} + i_t \times a_{\tanh}(W_{xC} x_t + W_{hC} h_{t-1} + b_C). \tag{8}$$

Finally, the output of the LSTM model is then calculated in the hidden state $h(t)$ calculated as

$$o_t = a_{\tanh}(W_{xo} x_t + W_{ho} h_{t-1} + b_o). \tag{9}$$

$$h_t = o_t \times a_{\tanh}(C_t). \tag{10}$$

2.2.6. Autoencoders

Autoencoder is a neural network that can learn efficient codings of unlabeled data, i.e for unsupervised learning [46], and is used for many problems such as feature detection and anomaly detection. The autoencoder is trained to learn two transform functions — encoder and decoder. The autoencoder learns an efficient representation (encoding) for a set of data, typically for dimensionality reduction. The transformation applied over the input raw features is the *encoder* and it is represented as a matrix $W_e \in \mathbb{R}^{b\times z}$ with $b \leq z$, such that for any $x \in \mathbb{R}^z$ the encoded vector is $x_b = W_e(x) \in \mathbb{R}^b$. The latent space, x_b, is a compressed representation of the original space in which the inputs are projected into a space of lower dimension which consists of features that cannot be interpreted directly from the original space. In addition, the *decoder* transforms the latent space features back into the raw features and is represented as $W_d \in \mathbb{R}^{z\times b}$, such that $x_e = W_d(x_b) = W_d(W_e(x))$. The objective function of the encoder–decoder (see Fig. 5), also called *the reconstruction loss*, is given by

$$\min \|x - x_e\|_2^2 = \min \|x - W_d(W_e(x))\|_2^2. \tag{11}$$

Thus, the objective is to minimize information loss in the latent space, enabling reconstruction of the original signal from the latent space.

2.3. Evaluation metrics

Battery fault detection classifiers are evaluated based on diverse metrics. Some of these metrics formulate as binary classification tasks, and have three possible outcomes: true positive (TP) is the number of times a fault/state is correctly detected, false positive (FP) is the number of times other faults are wrongly detected as a specific state, and false negative (FN) is the number of times a specific fault/state is wrongly detected as other fault. *Accuracy* is a commonly used evaluation metric and is defined as

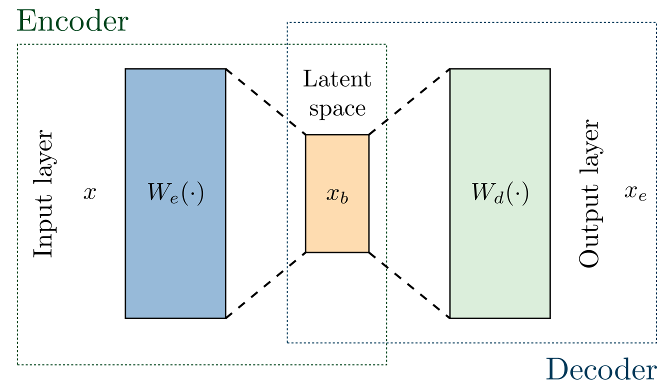

Fig. 5. General autoencoder — visualization of a latent space and its transformations.

$$\text{Accuracy} = \frac{\text{TP}}{\text{TP} + \text{FN} + \text{FP}} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}. \tag{12}$$

In this work we also use the F-measure metric, which is common in the information retrieval domain [47]. The F-measure is the harmonic mean of the *precision* and *recall* measures, and is given by

$$F\text{-measure} = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}, \tag{13}$$

where

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{14}$$

Another type of evaluation metrics are estimation error in regression models, which are common for battery diagnostic approaches. For these metrics $y[n]$ is the true observed value and $\hat{y}[n]$ is the algorithm predicted value at sample time n. There are four familiar error metrics that are used to test battery diagnostic and prognostic classifiers — mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE). The MSE is defined by the equation:

$$\text{MSE} = \frac{1}{N} \sum_{n=1}^{N} (y[n] - \hat{y}[n])^2 \quad , \tag{15}$$

and the RMSE is:

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (y[n] - \hat{y}[n])^2} \quad , \tag{16}$$

where N is the number of all data samples. Also, MAPE and MAE are defined by the next formulas:

$$\text{MAPE} = \frac{100\%}{N} \sum_{n=1}^{N} \left| \frac{y[n] - \hat{y}[n]}{y[n]} \right|, \tag{17}$$

$$\text{MAE} = \frac{1}{N} \sum_{n=1}^{N} | y[n] - \hat{y}[n] |. \tag{18}$$

3. Survey of DL techniques for battery faults in EV

This section reviews and analyzes recent works and trends related to fault diagnostics in EV battery. Section 3.1 describe general approaches for battery faults detection using DL techniques. In Section 3.2 the latest works using feed-forward neural networks are presented. Then, in Section 3.3 papers that examine the use of LSTM architecture for fault diagnostics are reviewed and analyzed. Later, Section 3.4 focuses on CNN-LSTM techniques for faults diagnostics. Finally, Section 3.5 presents other DL techniques for battery fault diagnostics such as CNN, autoencoders and attention mechanisms.

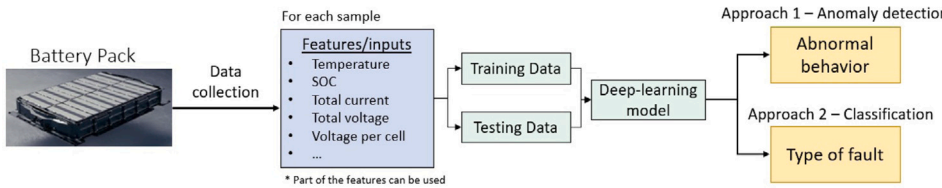

Fig. 6. DL techniques for Battery fault diagnostics — general approaches.

Table 1
DL models- advantages and disadvantages in battery fault detection.

Architecture	Advantages	Disadvantages
FNN	– Feature learning from raw data	– Prone to over-fitting with limited data
LSTM	– Ability to capture long-term dependencies in time series data – Effective in handling sequential and time series data	– May not capture spatial dependencies as well as CNN
CNN	– Effective in capturing spatial patterns in sensor data	– May not capture temporal dependencies as well as LSTM
ConvLSTM	– Captures both spatial and temporal dependencies	– Longer training time compared other architectures
Autoencoder	– Unsupervised learning – Dimensionality reduction – Anomaly detection – Reconstruction of input data	– Requires large amounts of unlabeled training data – May not generalize well to unseen data

3.1. DL techniques for battery fault diagnostics — general approaches

Fig. 6 illustrates a general flow chart depicting the use of deep learning models for battery fault diagnostics and prognostics. The process begins with data collection, where relevant time samples are gathered. The data includes various features such as battery temperature, state of charge (SOC), total current, total voltage, and voltage for each cell. It should be noted that different models may have different inputs, for example some models utilizing only temperature, others incorporating voltage combined with SOC and some contain other combinations. Following data collection, the dataset is split into training and testing subsets, and then fed into the deep learning model for training, validation, and inference processes. The purpose of this division is to evaluate the performance and generalization ability of the trained model.

Two main approaches are commonly employed for battery fault detection. The first approach is abnormal detection, wherein the training data consists only normal battery operation, and when an anomaly behavior is detected by the classifier, an alarm is triggered. Anomaly detection aims to identify rare or unusual instances in a dataset. The algorithm learns to identify patterns that deviate significantly from the norm. Moreover, Anomaly detection algorithms typically output a score or probability indicating the degree of anomaly for each instance.

The second approach is classification, where the model is trained using both normal and faulty data, which are labeled accordingly. the dataset is labeled, and the algorithm learns to assign the correct label to new instances based on the patterns observed in the labeled data. Classification can handle both balanced imbalanced datasets, but the focus is on correctly classifying instances into different classes.

The specific chosen DL model can be considered based on Table 1 which contains a general overview of the advantages and disadvantages of each neural network architecture for battery fault detection. It is important to note that the suitability of each architecture depends on the specific characteristics of the battery fault detection problem, available data, and computational resources.

3.2. Feed-forward neural networks for battery fault diagnostics

Some works that use FNN for fault and defect diagnosis of EV battery were published in the last couple of years. The first work which uses FNN [48] presents a big data statistical method for fault diagnosis of battery systems based on the data collected from Beijing Electric Vehicles Monitoring and Service Center. The analyzed fault is considered as abnormal changes of cell terminal voltages in a battery pack. The neural network is used to fit the distribution of faults caused by design flaws or intrinsic problems. One significant finding of the study is that the distribution and frequencies of fault occurrences are generally stable, with the exception of the winter season when the frequency of battery faults increases notably. More recently, research [49] has been published focusing on external short circuit faults during charge and discharge. The approach proposed in this study employs FNN to estimate the current flowing through the ESC cell. Additionally, an electro-thermal model is utilized to estimate the temperature of the ESC cells. In work [50] voltage fluctuation of battery pack is collected during battery charging and discharging experiment under noisy environment. To improve the quality of the voltage data, the researchers apply a discrete wavelet transform to eliminate noise from the voltage signal. After preprocessing the voltage data, several features are extracted, including voltage, voltage difference, and covariance matrix. These features serve as input to neural networks, which are trained to classify the fault status of the battery pack. The classification categories include "no failure", "slight failure", "medium failure", and "serious failure". In [51] extreme learning machine NN is developed to capture the temperature behavior of batteries under ESC conditions. The experiments were done on various battery state of charge and temperatures. Based on these tests an ESC database is used to train the model which predict the temperature under ESC conditions. Since not all battery cells are equipped with temperature sensors, the temperature of these cells needs to be estimated using other available signals. In this work, the current signals are used to estimate the temperature of the battery cells. In the work [52], a failure diagnosis technique for LIBs is proposed using a multi-layer perceptron (MLP) classifier. The technique leverages voltage and current responses from LIBs experiencing various types of failures. These responses are converted into partial charging curves, which serve as input for the training process of the MLP classifier. The model achieves good performance for both healthy cases and for four different abuse cases.

In paper [53], an early warning model for EV charging is proposed with the focus on the maximum voltage of the battery pack. An FNN is used to predict the EV charging process and to monitor the changes in the battery charging voltage. The identification of abnormal voltage value is very accurate and can effectively prevent thermal runaway caused by poor battery balance during charging. Also, paper [54] studies the response of the voltage signal of each cell in a battery system in relation to the change in fault degree during the charging or discharging process. The authors employ an Extreme Learning Machine (ELM) as the underlying neural network model, and the ELM is optimized using a Genetic Algorithm (GA). In addition, study [55] developed a fault warning method for an EV charging process based on

Table 2
Summary of Feed-forward Neural Network models for battery fault diagnostics.

Ref.	Fault type	Inputs	Objective & Metric	Data	More comments
[48]	Abnormal changes of cells terminal voltage	Cells terminal voltage	Outlier detection	Beijing electric vehicles monitoring and service center	–
[49]	ESC cells	Voltage of SC cells	Min MSE	Experimental platform	Electro-thermal model is used to estimate temperature
[50]	Connection fault	Voltage of battery pack	Accuracy	Experimental platform	Wavelet transform is used
[51]	Temperature under ESC	Current signals	RMSE	Experimental platform	The NN is based extreme learning machine
[52]	Abuse modes	Charging curves (voltage, SOC)	Accuracy	Charging test platform	–
[53]	Overcharge (abnormal voltage)	Voltage, SOC, temperature	Accuracy	Fast and slow charging tests	Grey Wolf Optimization is used
[54]	Abnormal voltage	Cells voltage	Experimental platform	Genetic algorithm is used	
[55]	Overcharge and temperature faults	Voltage, current, temperature, SOC	Pearson coefficient	EV charging process data	Deep belief network is used
[56]	Communication and sensor faults	Voltage, current, SOC, temperature	F-measure & RMSE	MATLAB Simulations	Residual network is used
[57]	Overcharge	ECM	RMSE	Data collected from an aging experiment	Mass of Lithium plating is detected

a deep belief network. The network uses various features as inputs, such as voltage, current, temperature and SOC and predicts the charging voltage and current which are compared to the real measurement. Then, by using Pearson coefficient calculation a voltage and current fault warning may be activated. Finally, work [56] provides a residual network for false battery data identification and classification system which focuses on faulty battery sensors.

Table 2 presents a summary of research involving the utilization of feed-forward neural networks for EV battery diagnostics.

3.3. LSTM & CNN for battery fault diagnostics

LSTM is used for battery diagnostics and prognostics since it is considered a good candidate for time-series applications. The first work to use LSTM is [58] which presents a novel approach for voltage prediction and detecting potential abnormal voltage fluctuations. This is done by using past samples of cells and pack voltage combined with weather and driver's behaviors in order to predict the next voltage sample. In case the prediction is not aligned with the real values abnormality, alarm may be activated. Real-world operational data of an electric taxi is acquired from the Service and Management Center for electric vehicles(SMC-EV) in Beijing. This data contains fifteen parameters, and, in order to prevent overfitting feature selection is suggested. The chosen features are voltage (cell and pack), SOC and vehicle speed. The authors in [59] presented battery fault diagnosis based on voltage abnormality by combining LSTM and equivalent circuit model (ECM) of the battery. The main contribution of this work is the comparison of the LSTM prediction to the ECM. The method achieves accurate fault diagnosis for potential battery cell failure. Also, by using the influence of the driver behavior, the method able to present early thermal runaway warning. The data that was used in this work was taken from the National Monitoring and Management Center for New Energy Vehicles (NMMC-NEV) in China. The chosen vehicles were divided into three groups — normal, with potential failures, and with TR. Work [60] also demonstrates the detection of Abnormal voltage faults in EVs using LSTM. The method uses four time-series signals of voltage, current, speed and power as inputs, and the output is the abnormal voltage type. These types are classified to 'swell', 'sag', 'line-to-ground' and 'line-to-line'. Another work that use LSTM is [61]. In this work fault detection method for a liquid leakage and liquid intrusion detection system is presented.

In the past decade, the utilization of CNN algorithms has increasingly become prevalent in the field of EV fault detection and classification. In paper [62] CNN is used to detect and classify inaccurate data caused by sensor faults and communication failures. The battery data are voltage, current and temperature signals and the fault classified as offset, stuck, delay and replay. The F-measure performance is 0.98 and is better than other classification techniques. In work [63] electrical consistency and synchronization between cells are quantified as correlation coefficients. Then, these coefficients are converted to images which are the inputs to CNN which extract fault indications. A pack of four LIB cells is used in the experiment which include three optional faults ESC, ISC and thermal fault. Experimental results show that the proposed framework can accurately and reliably diagnose various battery faults and reach to more than 99% accuracy. In addition, research [64] developed a CNN architecture to detect lithium plating quantity using voltage and current signals as inputs. The lithium plating detection accuracy is higher than 98% and the quantity of the lithium plating is predicted with small RMSE. The network training and testing is done in a wide range of temperatures and charging rates. Table 3 presents a summary of research involving the utilization of LSTM or CNN architectures for EV battery diagnostics.

3.4. Convolutional-LSTM networks for battery fault diagnostics

Lately, Convolutional neural network and LSTM were combined to produce an architecture named ConvLSTM which has the advantages of both performing feature extraction and time-series analysis. The work which first used this architecture for fault prognosis is [66] which proposes a model of battery pack based on ConvLSTM to ensure the safety of EVs. The network first layer is a one dimensional CNN layer and then all other layers, except the last one, are LSTM layers. Another contribution of this work is the use of data augmentation. In paper [67] thermal runaway prognosis algorithm is suggested. The algorithm is based on ConvLSTM which can predict the battery temperature eight-minute ahead with mean-relative-error of 0.28%. Additionally, all the data is compressed using principal component analysis as part of preprocess stage. The predicted temperature is compared to the real temperature and if abnormal heat generation is discovered an alert for TR is provided. The verification results shows that the method can detect of thermal runaway event 27-min-ahead. In work [68] an EV charging process early warning protection method is developed. The method monitors an EV charging system which provides real-time early warning of EV overcharging by predicting potential risks using ConvLSTM network. Study [69] proposes a method to predict TRP in battery modules. The method forecasts TRP under different state of charge using LSTM and 3-D CNN layers. The dataset is established using experimental data, simulation data, and public datasets. Early warning strategy is based on comparison the model output to real temperature. Another work is [70] which proposes a fault diagnosis method for lithium-ion batteries in electric vehicles

Table 3
Summary of LSTM or CNN models for battery fault diagnostics (see [65]).

	Ref.	Fault type	Inputs	Objective & Metric	Data	More comments
LSTM	[58]	Abnormal voltage fluctuations	Voltage (cell and pack), soc and vehicle speed	MAPE	Beijing SMC-EV	Feature selection is used
	[59]	Abnormal voltage fluctuations	Voltage (cell and total), SOC and current	MSE	NMMC-NEV China	ECM model is used
	[60]	Abnormal voltage fluctuations	Voltage, current, speed and power	MAPE, RMSE	EV prototype test bench	–
	[61]	Liquid leakage and intrusion	Liquid sensitive sensors	Accuracy	Prototype laboratory stand	Correlation coefficient is used to fed the CNN
	[65]	Overcharge	Voltage, current, SOC, temperature	RMSE	Battery cell test	Lithium plating prevention
CNN	[62]	Sensor faults and communication failures	Voltage, current and temperature	F-measure	Battery cell simulation model (MATLAB)	–
	[63]	ESC, ISC, thermal faults	Voltage	Accuracy	Battery pack test	–
	[64]	Lithium plating detection & quantity	Voltage and current signals	Accuracy, RMSE	Tests with different range of temperatures and charging rates	–

Table 4
Summary of ConvLSTM models for battery fault diagnostics.

Ref.	Fault type	Inputs	Objective & Metric	Data	More comments
[66]	TR, ISC, inconsistent, abnormal resistance	Voltage pack, current pack, SOC, temperature	F-measure	Battery pack of ten EVs	Data augment for generation more data is used
[67]	TR	Weather, EV state, driving behavior, voltage, current, temperature	Mean-relative-error	NMMC-NEV	Principal component analysis is used to reduce the computing time
[68]	Overcharging	Voltage, current, temperature	RMSE, MAPE	EV charging data through actual charging stations	Sliding window is used
[69]	TRP	Voltage, current, SoC , temperature and thermal images	MAE, MAPE	Experimental data, simulation data, and public datasets	Equivalent circuit model is used
[70]	Overcharging, voltage abnormal, insulation	Voltage, current, SoC	RMSE	NMMC-NEV	wavelet transform is used
[71]	Voltage abnormal	Voltage under different temperature	RMSE	Experimental setup of 8 Real LIB	Correlation coefficient is used
[72]	TRP	Voltage TR distance, temperature, current, voltage, soc	MAE	Experimental and simulation data	TR probability is optimized using sparrow search algorithm

based on multi-method fusion. This method discover what are the features of the vehicle that have a large influence on the battery fault which are later used by ConvLSTM. The method has high accuracy and reduces the response time of fault diagnosis. Also, paper [71] uses ConvLSTM model to predict the voltage data of each battery cell in the battery module. Then, correlation coefficient is used to analyze the predicted values with the historical values and determine whether any battery has faults. Finally, [72] suggests a method to predict TRP of battery modules during uncertainty conditions by three steps. First, data collection is done by creating TR events in different cells and with variable SoC on 25 sets of experiments and 130 sets of simulations (based on ECM model). Second, TR probability is optimized using sparrow search algorithm. Third, prediction model based on Conv-LSTM is trained using various inputs and TR probability which outputs the future temperature. Table 4 presents a summary of research involving the utilization of ConvLSTM architectures for EV battery diagnostics.

3.5. More DL techniques for battery fault diagnostics

In addition to the mentioned networks in previous subsections there are other types of deep learning models used for battery diagnostics and prognostics. Some of these models are autoencoders which were discussed in 2.2.6, others are state-of-the-art techniques such as attention [73] and transformers [74] which focus on connections and dependencies in the time series input signals. In [75] a nonlinear autoregressive exogenous (NARAX) neural network is used for voltage prediction and for providing early fault warning for the battery by identifying abnormal voltage. Works [76,77] focus on the use of autoencoder networks in order to find abnormality in the battery cell level. In paper [76] normal charging sequences were used to train various autoencoder networks if a reconstructed signal in the test data has high error it means that the cell is inconsistent with other cells. It has been shown that, the best autoencoder model contains convolution and LSTM layers. Similar, in [77] autoencoder is used on real EVs to recognize abnormality during charging. The autoencoder network has interpretable modules which provide supplementary information on the battery features. The proposed method is tested on dataset from the National Bigdata Alliance Open Laboratory of NEVs (NBAOLN) which contains over nine million EVs. The method is compared to variational and regular autoencoders and outperforms both methods. During 2023, three new works published which use attention and transformer concepts to detect faults in battery. In work [78] the inputs of voltage and temperature are used to predict thermal runaway using an attention mechanism. First, wavelet transform is used to extract time–frequency features from the inputs. Then, the history data of these features are used to predict the next sample using residual deep neural network with attention. Finally, alarming indicators are suggested for safe range. It was shown on real life data that thermal runaway can be predicated 8–13 min ahead. The authors in [79] suggest using a year long real-world EV temperature data to train a neural network which containing Self-attention mechanism. The network output performs well on temperature prediction of battery systems for all seasons and provides sufficient time to take urgent actions in case of abnormal behaviors. Last, paper [80] proposes a reconstruction-based model for ISC detection in battery packs by combining transformer and LSTM. The model's output is the reconstructed value of the voltage data based on its history inputs which helps to detect ISC in case of anomalies. In addition, false-positive clipping method is used to improve the

Table 5
Summary of other DL models for battery fault diagnostics.

Ref.	Fault type	Inputs	Objective & Metric	Data	More comments
[75]	Voltage abnormal	Voltage	RMSE, MAE	Cells cycled at eight experimental temperatures	NARX model is used
[76]	Inconsistency during charging	Voltage, SOC	MAE	96 battery cells	various autoencoder models are used
[77]	Voltage abnormality during charging	Voltage, SOC, current	RMSE	NBAOLN	interpretable autoencoder is used
[78]	Thermal runaway	Voltage, temperature	combined relative error	Real-world operational data of 10 EVs (2 with TR)	Attention with residual is used, and wavelet transform is used as part of pre and post precess
[79]	Temperature anomaly	Temperature	MRE, Absolute error	A year long real-world operational dataset of an electric taxi	Self-attention mechanism is used
[80]	Internal short circuit detection	Voltage	F-measure	battery pack data with different type of power resistors	Transformer and long short-term memory are used

preliminary results of the network. A summary of these works is given in Table 5.

4. Recent trends, challenges directions & opportunities

4.1. Trends based on survey summary

The literature survey presented in the above section (Section 3) clearly shows that engineers and researchers are using DL techniques more often in fault diagnostic applications for EV battery. Since 2019, we see a steady growth in the number of publications describing DL techniques for these applications, as shown in Fig. 7. The main keywords we used for searching papers are summarized in Table 6. We used several of the most common fault types and DL methods during our literature search. The search was also restricted to the title, abstract, and keywords fields. Furthermore, more than 70% of the authors of the reviewed papers in this survey are mainly from academic institutes in China, while around 18% of the other authors are from USA as can be seen in Fig. 8.

We have classified the research papers surveyed in our work based on their fault diagnostic domain. A diagrammatic representation of the same is shown in Fig. 9. The majority of publications have been about general battery pack issues such as abnormal voltage (29%). Also, detection of increasing temperature (mainly TR) are considered very popular (26%). Other issues such as SC and charging faults are common (19% each) as well, while BMS controller issues are less popular (9%). The papers have also been categorized based on the DL model used. It is found that most diagnostics have been applied on Feed-forward Neural Network (FNN) techniques (30%). The second most popular architecture is based on ConvLSTM (23%). less than 7% of the techniques surveyed were used with auto-encoder and only 10% used with attention and transformers, an indication that these new DL approaches are still not widely used. This information can be seen in Fig. 10.

Moreover, the research papers surveyed in this work were classified based on the classifiers' inputs. A diagrammatic representation of the same is shown in Fig. 11. The majority of publications used cell voltage as the input. Also, many methods used current, temperature and SOC as a feature. Nevertheless, current temperature and SOC were used as part of multiple features while cell voltage was used sometimes as a single feature.

Finally, Fig. 12 illustrates the DL architectures utilized for each battery fault type. For example, it can be observed that the ConvLSTM architecture is commonly used for Short Circuit (SC) faults.

4.2. Main challenges

There are various challenges that need to be addressed when implementing DL for fault diagnosis for LIBs. Some of the challenges are based on [11], and provided below in a comprehensive manner:

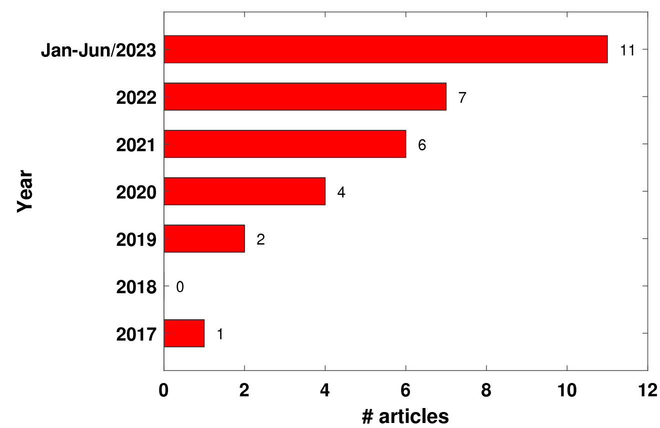

Fig. 7. Year-wise distribution of publications on EV battery fault diagnostics and prognostics using deep learning.

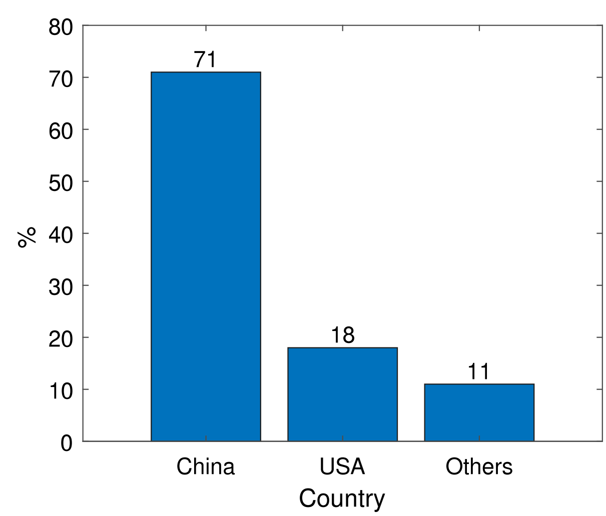

Fig. 8. Country-wise distribution of publications on EV battery fault diagnostics and prognostics using deep learning.

- Lack of knowledge regarding faults in EV batteries is a significant challenge. Firstly, there is incomplete understanding of the mechanisms behind faults in LIBs. Furthermore, there is a lack of standardization and regulation for testing battery faults. Additionally, most existing mathematical models are unable to accurately depict the behavior of different faults. Moreover, determining the cause of a fault is often unclear, as different conditions can lead to the same anomaly or fault. These factors collectively present

Table 6
Keywords for different application areas.

Primary expression	Secondary expressions	Third expressions
"EV battery faults"	"Deep Learning"	"LSTM"
AND	OR	"CNN"
"diagnostics"	"DL"	"Short Circuit"
AND/OR	OR	"Thermal Runaway" AND "TRP"
"prognostics"	"Neural Network"	"BMS"
		"Charging"

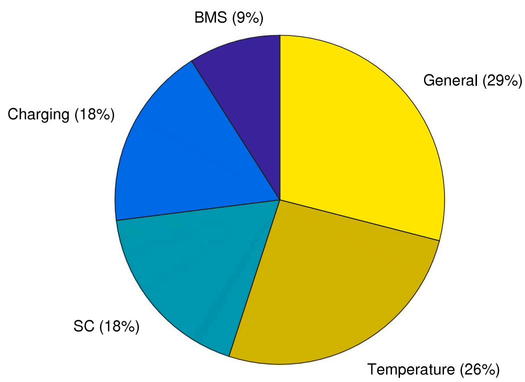

Fig. 9. Classification of papers based on the characteristics of the battery fault. Note that the category 'General' includes abnormal voltage behavior.

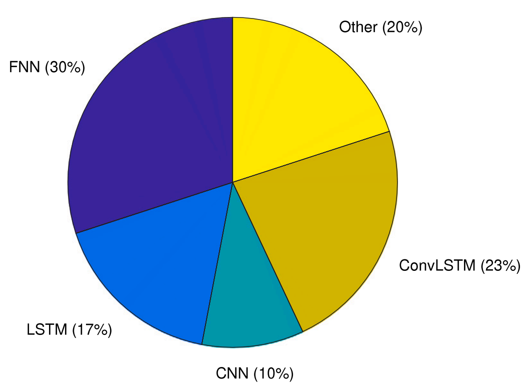

Fig. 10. Classification of papers based on the characteristics of the DL model used.

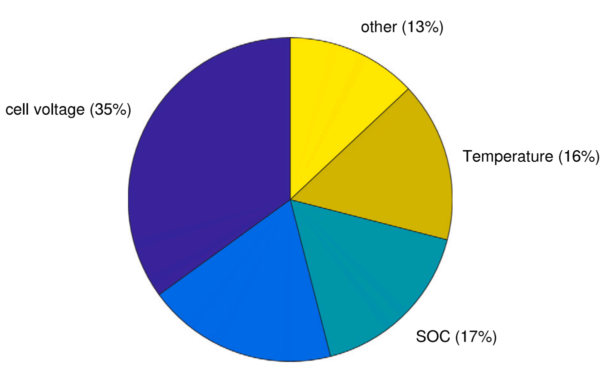

Fig. 11. Classification of papers based on the signal inputs to the DL model.

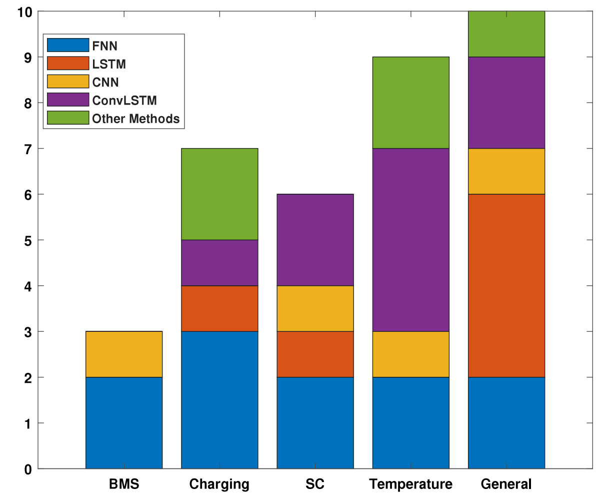

Fig. 12. DL architectures utilized for each battery fault type.

difficulties when employing data-driven methods. Nonetheless, since the underlying physics of faults remain uncertain, DL methods, which can autonomously learn features from data, show promising potential for such applications.

- One of the major hurdles faced by data-driven methods in battery fault diagnostics is the scarcity of relevant features that can be utilized. Typically, only temperature, voltage, and current are accessible as features. This absence of features related to the electro-chemical behavior of the battery significantly restricts the analysis of its internal state. It is important to note that in certain situations, these features are measured at the battery pack level rather than for each individual cell. As a result, accurately identifying the faulty cell becomes challenging without knowledge at the cell level. In certain instances, faults may remain undetected until a complete system failure is experienced, which might be measured as noise or a minor impact on the entire battery level.
- An additional significant limitation is the availability of data containing faults. Collecting data with faults is a difficult and rare task. The majority of the available data primarily consists of normal states, and there is a lack of publicly accessible data that includes faults. This scarcity of labeled fault data poses a challenge when developing and training models for fault detection and analysis.
  Moreover, another challenge arises from the fact that some of the recorded data are based on simulations that do not adequately simulate faults or may not simulate them at all. Training various ML approaches on such data can result in overfitting and may lead to failure when applied to real-life scenarios. It highlights the need for reliable simulation models and realistic data that accurately represents the occurrence of faults in order to develop robust and effective ML models for fault detection and analysis.
- The detection process poses a critical challenge in fault analysis. Firstly, determining an appropriate threshold that minimizes both false alarms and missed detections is difficult. Finding the right balance is crucial to ensure accurate identification of faults without an excessive number of false alarms or overlooking genuine faults. Additionally, the timing of the detection is an important obstacle. If an algorithm detects a fault only after a thermal runaway (TR) event has already commenced, its relevance and effectiveness in preventing further damage are diminished. It is far more valuable to detect faults minutes or hours prior to the event's initiation, enabling proactive measures to mitigate the risks associated with the fault.

A summary of the challenges are presented in Table 7.

Table 7
Open challenges when implementing DL for EV battery fault diagnosis.

Category	Challenges
Lack of knowledge	✓ No clear standardization and regulation for battery fault tests ✓ Faults mechanisms are not fully understood ✓ Mathematical models cannot describe the behavior of different faults
Features	✓ Hard to locate faulty cell when only battery pack-level is measured ✓ Features that related to the electro-chemical behavior are not available
Data with faults	✓ Very rare and challenging to collect ✓ No public data with labeled faults ✓ Most data sets contain only single fault
Detection process	✓ Hard to choose a threshold with minimum false alarm and miss detection ✓ The time of the detection

4.3. Opportunities and future directions

In this subsection, some opportunities and future directions related to the use of DL models for EV battery faults are identified by looking at concepts which use DL, but have not yet been considered.

4.3.1. Explainable artificial intelligence

One of the downsides of many deep learning algorithms is their "black box" nature. This means that these algorithms are extremely hard to explain, and for the most part they cannot be completely understood, even by domain experts. If users consider a model to be a black-box, they will not always trust its predictions, and therefore will be reluctant to use it. Furthermore, DNNs are very complex black-box models, even for AI experts, since their architecture is designed using trial and error processes, and they may consist of hundreds of layers and millions of parameters. Considering this challenge, the main goal of Explainable Artificial intelligence (XAI) is to allow researchers, developers, and users to better understand the results of machine learning models, while preserving their high performance and accuracy. Various XAI techniques can be found in the literature [81,82], most of these are dedicated to DL models. In [83] the term *explanation* is defined as follows: additional information, generated by an external algorithm (or by the classifier itself), that describes the relevant features of an input instance, for a particular output. The use of XAI for power and energy systems is considered a new concept, and recently many applications implement it for improving the transparency of their DL models [84]. Currently, XAI is used to explain state of health (SOH) estimator of lithium-ion battery [85], also the authors in [86] suggest to embrace XAI for battery prognostics and health management. Accordingly, XAI can be very effective when DL techniques are used for EV battery faults detection. This idea, implemented in the battery fault diagnostics and prognostics, is illustrated in Fig. 13. Also, a specific example for evaluating the performance of battery health is given in Fig. 14. In this figure, XAI is used to inform the user which features are important.

4.3.2. Neural architecture search

Despite their evident success, DNN are very complex models since their architecture is designed using trial and error processes and they may consist of hundreds of layers and millions of parameters [87]. Accordingly, the problem of finding the optimal architecture can be considered as a problem that consists of high dimensional solutions. In addition, the development of DL models is computationally intensive with no guarantees on compute limits and performance, thus power experts may limit their practical usefulness [87]. Considering the above gap, there is high motivation to develop efficient methods with low-complexity to find optimal battery faults detection classifiers using

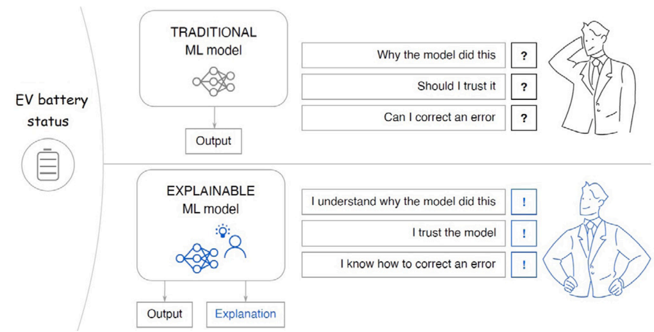

Fig. 13. Concept of XAI for EV battery diagnostic application.

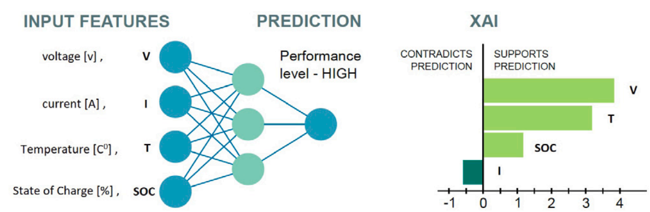

Fig. 14. Example of a classifier model with XAI for evaluating the performance of battery health. The XAI technique informs the user which features are more relevant and important to the classifier's decision.

Neural Architecture Search (NAS) technique [88]. By using NAS techniques a DNN model with high accuracy can be efficiently found from large search space of possible network topologies and operations using limited resources and with minimal human intervention. This will allow to find faster models which are robust and generalize well to many real-world scenarios.

4.3.3. Physics-informed neural networks

Although DL is an effective method for accurately detecting battery faults in diagnosis, there is still a lack of understanding regarding the underlying mechanisms of battery failure. To address this issue, an alternative approach to detecting battery failures is suggested: the use of Physics-informed neural networks (PINN). PINN are neural networks that are trained to solve supervised learning tasks while incorporating physical principles into their loss function, which is described by general nonlinear partial differential equations [89]. This approach ensures that the model's predictions not only fit the observed data but also adhere to the governing equations of the underlying physical processes. By leveraging the physical knowledge of battery failure, PINN can provide accurate predictions even with limited data. Recently, PINN has been applied to lithium-ion batteries for tasks such as temperature state prediction and aging analysis [90].

4.3.4. Public data-set of battery faults

Another important future research direction is building robust and public data-sets of normal and abnormal battery behavior. Presently, a core obstacle that prevents the direct comparison of LIBs diagnostics DL techniques is the lack of a standard database that can be used as for benchmarking. Considering this gap, we propose to create a public data-set that is based on real experiments of different EV battery faults, with focus on TR events. In addition, each fault will be recorded as a dimensional signal which include the next features: voltage of each cell, SOC, total current and battery's temperature. Furthermore, an open-source software package that includes deep learning classifiers should be provide for comparison and as a benchmark for other state-of-the-art algorithms. Note that this direction is new for many applications in power and energy such as power quality disturbances [91], synchronous motor electrical faults [92] and frequency disturbance events [93].

4.3.5. Early detection of TRP - from minutes to hours

The occurrence of thermal runaway, which can result in explosions, is often initiated by minor defects that are challenging to detect during their initial stages. These defects can develop unnoticed for extended periods, potentially spanning weeks. However, once they reach a critical level, they undergo a sudden eruption, releasing an immense amount of heat and causing temperatures to rapidly soar beyond 800 degrees Celsius within seconds. This violent reaction is accompanied by the release of hazardous gases, fire, heat and shrapnel. Due to its self-sustaining nature within the battery cell, the thermal runaway reaction is exceptionally difficult to extinguish. While many DL techniques can facilitate early detection of thermal runaway events, the time between detection and the actual event is often quite short. Consequently, it is unlikely that the event can be prevented entirely. However, the detected information can be utilized to issue timely alerts, allowing individuals to take appropriate actions, such as isolating the EV from potential hazards. For instance, in study [59], an alert was generated approximately 150 s prior to the thermal runaway occurrence, while another approach, suggested by Beijing Institute of Technology, in [67] demonstrated a considerably long early detection time of 27 min before the thermal runaway prognosis. Nevertheless, the ideal scenario would involve receiving warnings several hours in advance to effectively prevent the event from occurring. To conclude, Exploring how to achieve very early alerts, hours before the thermal runaway event, utilizing DL methods must be considered.

4.3.6. Edge AI

Presently, many research neglect the consideration of computation time and memory limitations when designing DL architectures. These works typically assume that all data can be processed with unlimited resources. However, this assumption does not align with the reality of BMS controllers, as they operate under resource-constrained environments and may not have consistent access to cloud-based centralized computing. In light of this, exploring the potential of edge AI becomes crucial, where AI computations are performed directly on the EV where the data is collected. The challenges and obstacles associated with edge AI are multifaceted. For instance, there are limitations in terms of computational capabilities and real-time processing on resource-constrained devices. Memory constraints also pose a significant challenge for running complex DL models directly on the EV. Consequently, a careful examination of edge AI is necessary to overcome these limitations and develop efficient solutions. In addition, hybrid computing, which combines local computing on the EV and offloading certain tasks to cloud-based resources, presents an interesting research direction. This approach aims to strike a balance between utilizing local resources for real-time computation and leveraging cloud computing for more intensive tasks. Exploring the potential of hybrid computing can help overcome the challenges associated with edge AI and further enhance the performance and efficiency of AI applications in EVs.

5. Conclusion

The rapid growth of electric vehicles has highlighted the need for effective diagnostic and prognostic techniques for EV battery faults. As part of this trend, deep learning algorithms have been implemented in several works in this domain over the last several years. This paper provides an overview of the state-of-the-art research on using deep learning for EV battery faults detection, while addressing the associated challenges and opportunities. The review then presents a comprehensive survey of various deep learning approaches employed in EV battery fault diagnostics and prognostics. The reviewed papers have been selected following an in-depth content analysis of various sources, as detailed in Section 4.1. This analysis reveals interesting trends in the current research, and may help one understand under which conditions the different DL techniques are used. Specifically, the data shows that ConvLSTM and FNN are the most widely used DL techniques. Furthermore, DL algorithms are used, more often to find abnormal temperature and abnormal voltage behavior. Another important aspect covered in this work is the challenges and limitations of adopting and implementing DL techniques in the field of battery faults. While DL can improve the alerts, there are still obstacles that should be considered. Some of these challenges are lack of knowledge on how to model faults, availability of features, lack of data, and detection time which is not early enough. In addition, potential opportunities and future research directions were provided. The suggested future research areas are: the availability and quality of labeled training data, the explainability of DL models, model robustness and generalization to real-world scenarios, computational requirements, and the integration of DL techniques into practical EVs which may have memory limitations.

In conclusion, this survey emphasizes the significance of deep learning techniques for EV battery fault diagnostics and prognostics. It provides a comprehensive literature review of existing approaches, identifies the challenges involved, and highlights the opportunities for leveraging deep learning in this domain. The findings can guide researchers, battery experts and stakeholders in further advancing the field of EV battery fault diagnostics and prognostics, leading to improved safety, reliability, and performance of EV batteries.

CRediT authorship contribution statement

Ram Machlev: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing.

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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