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REVIEW ARTICLE

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Machine learning for fault diagnosis of high-speed train traction systems: A review

Abstract High-speed trains (HSTs) have the advantages of comfort, efficiency, and convenience and have gradually become the mainstream means of transportation. As the operating scale of HSTs continues to increase, ensuring their safety and reliability has become more imperative. As the core component of HST, the reliability of the traction system has a substantially influence on the train. During the long-term operation of HSTs, the core components of the traction system will inevitably experience different degrees of performance degradation and cause various failures, thus threatening the running safety of the train. Therefore, performing fault monitoring and diagnosis on the traction system of the HST is necessary. In recent years, machine learning has been widely used in various pattern recognition tasks and has demonstrated an excellent performance in traction system fault diagnosis. Machine learning has made considerably advancements in traction system fault diagnosis; however, a comprehensive systematic review is still lacking in this field. This paper primarily aims to review the research and application of machine learning in the field of traction system fault diagnosis and assumes the future development blueprint. First, the structure and function of the HST traction system are briefly introduced. Then, the research and application of machine learning in traction system fault diagnosis are comprehensively and systematically reviewed. Finally, the challenges for accurate fault diagnosis under actual operating conditions are revealed, and the future research trends of machine learning in traction systems are discussed.

Keywords high-speed train, traction systems, machine learning, fault diagnosis

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1 Introduction

High-speed train (HST) is an epoch-making means of transportation, demonstrating unparalleled advantages over traditional trains considering comfort, convenience, and efficiency (Cheng et al., 2015; Yang et al., 2018). At present, China has built the world's largest high-speed railway network with the longest operating mileage. By 2022, the operating mileage of China's high-speed railways has exceeded 40000 km (Xu et al., 2018; Lawrence et al., 2019). In addition, high-speed railways have achieved rapid development in other countries worldwide (Carvalho et al., 2017). China railway high-speed (CRH) series electric multiple unit (EMU) trains have become the main rail transportation for traveling in China.

The safety and reliability of HSTs have become the primary concern with the increase in the operating mileage of HSTs (Liu and Han, 2012; Brahimi et al., 2016; Zang et al., 2019). An HST is a large and complex electromechanical coupling system. If the key components of an HST fail but are not found and repaired immediately, then such a phenomenon may lead to severe accidents (Peng et al., 2019; 2020a; Liu et al., 2021). In particular, as the core component of HSTs, the traction system mainly comprises high-voltage electrical equipment, traction transformers, traction converters, and traction motors (Chen et al., 2019; Chen and Jiang, 2020). The traction system is the power source of the HST and is known as the "heart" of the HST. Therefore, the reliability of the traction system is crucial to ensure the safe operation of HSTs. However, during the long-term operation of HSTs, the core components of the traction system will inevitably experience different degrees of performance degradation and cause various failures, thus threatening the running safety of the train (Moosavi et al., 2012a; 2012b; Cheng and Yao, 2018; Khamidov and Grishchenko, 2021). For example, traction motors are prone to failures, such as broken rotor bar, air gap eccentricity, and inter-turn short circuits, which will cause HSTs to slow down or even stop suddenly (Tran et al., 2013; Peng et al., 2020a). Therefore, monitoring and diagnosing the health status of the traction system are of considerable importance. These tasks can be mainly divided into two parts: 1) monitoring the health status, which primarily identifies whether the traction system is running normally; and 2) diagnosing fault categories, which mainly identifies the type of fault occurrence in the traction system.

In the past 20 years, machine learning technology has shown excellent performance in many fields (Kotsiantis et al., 2006; Jordan and Mitchell, 2015); therefore, this technology has received extensive attention from researchers in the field of fault diagnosis. A variety of machine learning-based mechanical fault diagnosis algorithms have been proposed and achieved satisfactory performance in practical applications (Liu et al., 2013; Han and Jiang, 2016). These algorithms typically use the expert experience to extract valuable features from historical data and then employ classifiers (such as support vector machine (SVM) and artificial neural network (ANN)) to obtain fault categories (Moosavi et al., 2012a; 2012b; Ren et al., 2016). A large amount of historical data is collected with the operation scale expansion of HSTs, providing the data basis for data-driven machine learning algorithms. Therefore, scholars also designed a variety of traction system fault diagnosis methods based on machine learning according to the characteristics of the HST traction system (Sun et al., 2017; Cheng and Yao, 2018; Li, 2021). The diagnostic model automatically maps the obtained features to the fault category space using machine learning algorithms, which markedly improves the intelligence level of HST monitoring and maintenance.

Since 2010, algorithms based on deep learning theory under the background of big data have revolutionized the research of fault diagnosis (Zhao et al., 2019; Lei et al., 2020). Traditional machine learning algorithms can identify the health status of machinery; however, their feature extraction process still mainly relies on expert experience. In addition, traditional machine learning algorithms cannot adapt to the increasing amount of data and have poor generalization under complex working conditions, resulting in a large performance bottleneck. Deep learning is the most promising branch of machine learning (LeCun et al., 2015). Owing to the substantial improvement of computer hardware performance, especially the rapid development of graphic processing unit (GPU) parallel computing, a series of breakthroughs, such as ResNet (residual network) (He et al., 2016), DeepLab (Chen et al., 2018), and region-based convolutional neural network (RCNN) (Ren et al., 2017), have been established in deep learning. These algorithms motivate the research and application of deep learning in the field of mechanical fault diagnosis and produce a series of achievements (Han et al., 2021b; Liu and Gryllias, 2022; Wang et al., 2022). Similarly, deep learning has also achieved excellent performance in fault diagnosis of the HST traction system (Gu and Huang, 2020; Xu et al., 2021a; 2021b). In these works, diagnostic models automatically obtain valuable information from large datasets and learn mapping functions in high-dimensional space to diagnose the health status of the traction system accurately. These systems can provide end-to-end automated diagnostic models in the context of intensifying amounts of data, freeing researchers from tedious feature engineering.

Machine and deep learning technologies have rapidly developed in the field of HST traction system fault diagnosis. However, most of these methods only achieve excellent performance under certain stable operating or laboratory conditions. HST is a large and complex electromechanical coupling system, and its operating conditions are also dynamically changed. Therefore, numerous challenges are still encountered for accurate fault diagnosis of key components of HSTs and some shortcomings in machine and deep learning technologies still exist, which must be further improved and optimized (Liu et al., 2018; Chen et al., 2020a). At present, some scholars have reviewed the fault diagnosis of the traction system. For example, Chen and Jiang (2020) conducted a review of condition monitoring and fault diagnosis for the traction system, discussing the current state of research. Chen et al. (2022) reviewed the application of data-driven methods to fault diagnosis of the traction system and discussed the advantages and disadvantages of different algorithms. However, these reviews do not focus on the development, applications, challenges, and future development trends of machine learning in the field of HST traction system fault diagnosis. At present, machine learning has been vigorously developed in the field of the traction system fault diagnosis. Therefore, comprehensively and systematically reviewing the research on fault diagnosis of traction systems based on machine learning, identifying the encountered challenges, and discussing future development trends are necessary.

Based on the above discussion, this paper briefly introduces the core components of the HST traction system and systematically reviews the development and application of machine and deep learning in the field of traction system fault diagnosis. Numerous challenges for accurate fault diagnosis are revealed considering the characteristics of HST traction system and the nature of machine learning algorithms. Finally, solutions to these challenges and future roadmaps are discussed. The paper is organized as follows. Section 2 describes the components of the HST traction system. Section 3 provides a detailed overview of the research on fault diagnosis of traction systems based on machine and deep learning. Section 4 presents the challenges and future prospects of existing fault diagnosis models. Section 5 summarizes this paper.

2 High-speed train traction system

As the core system of HSTs, an efficient and reliable traction system is the key to realizing high-speed safe operation (Chen and Jiang, 2020; Chen et al., 2022). At present, HSTs mainly use electric traction drives. The main function of the traction system is to obtain electrical energy from the overhead contact system (OCS) and then provide the suitable three-phase alternating current (AC) to the traction motor to facilitate the conversion of electrical energy into mechanical energy through the traction motor (Yang et al., 2010). The schematic of this system is shown in Fig. 1. Electric traction drive can be divided into two categories: Direct current (DC) and AC drives powered by DC and AC traction motors, respectively. Compared with the DC traction motor, the AC traction motor has the advantages of high power, high speed, small size, and simple and reliable structure. Therefore, most HSTs use the AC traction system. Taking CRH series EMU trains as an example, the traction system mainly adopts the AC-DC-AC electric drive mode (Li et al., 2019). The schematic of this system is shown in Fig. 2. The power car of the EMU obtains single-phase AC from the OCS through the pantograph and converts it into DC power by using the rectifier after being stepped down by the traction transformer. The DC power is then converted into three-phase AC power with adjustable voltage and frequency by the traction inverter to drive the traction motor to work normally (Guzinski et al., 2010). As mentioned above, the HST traction system mainly comprises high-voltage electrical equipment, traction transformers, traction converters, and traction motors. The main function of high-voltage electrical appliances is to realize the power supply from the OCS to the traction

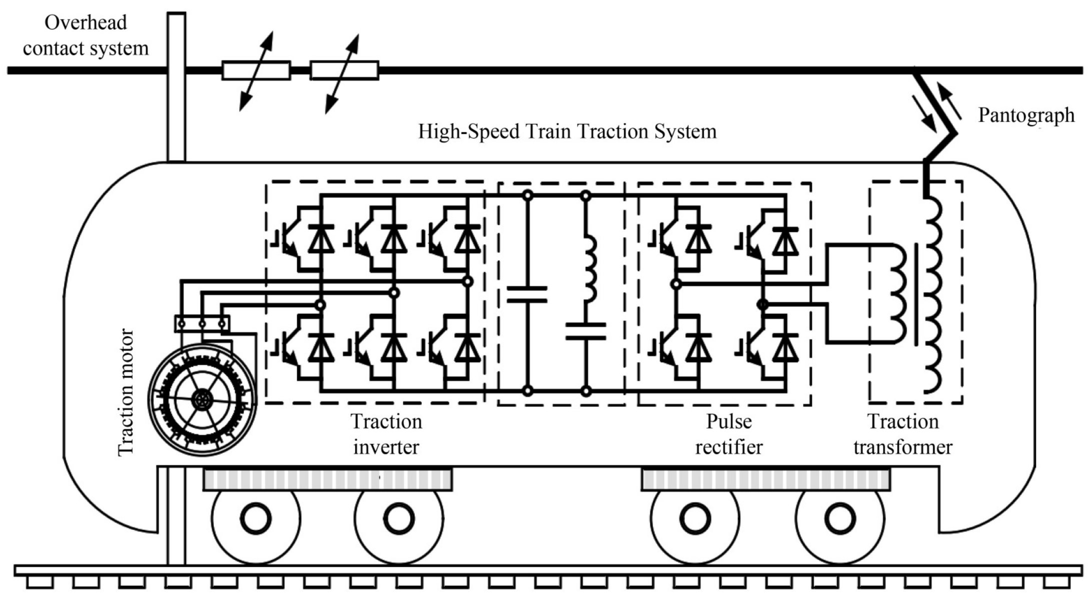

Fig. 1 Schematic of high-speed train traction system architecture.

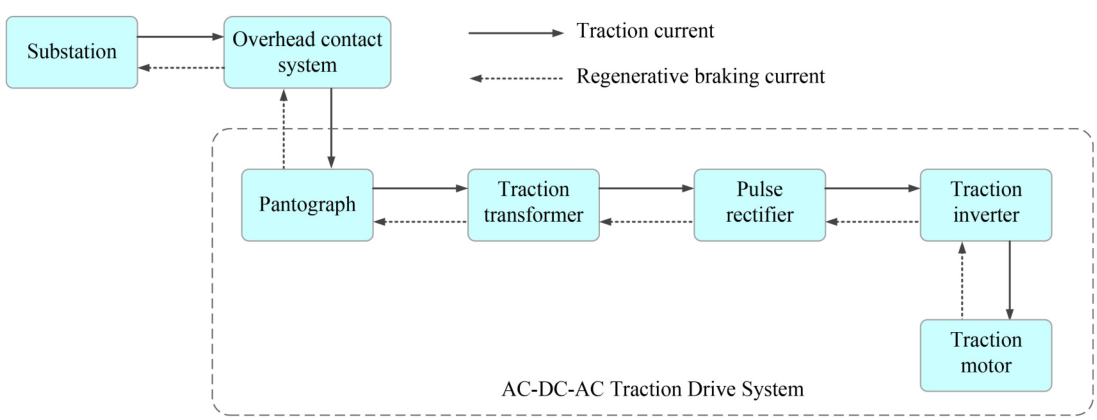

Fig. 2 Schematic of AC-DC-AC traction drive system.

transformer, which mainly includes pantographs, main circuit breakers, and arresters. The core components of the traction system and their common faults will be comprehensively introduced below.

2.1 Pantograph

The pantograph is a component that obtains electrical energy from the OCS, which is installed on the top of the electric traction vehicle. The pantograph has a special lifting mechanism; therefore, it can be controllably contacted and disengaged from the OCS (Kulkarni et al., 2017). The carbon strips of pantograph are in direct contact with the OCS during its operation, and ensuring good contact regardless of vehicle motion is necessary. HSTs mainly use single-arm pantographs, which mainly include the pantograph collector head, base frame, tie bar, lower arm, upper arm, and collector strip. The pantograph is often affected by vibration, shock, and aerodynamic load due to the harsh working environment, thus increasing its tendency to performance degradation and various failures (Karakose et al., 2017; Shi et al., 2020). For example, considering the upper arm jacking tube crack failure, the upper arm jacking tube mainly bears the vibration and impact between the pantograph collector head and the OCS, thus easily causing fatigue failure. Collector strip holder crack failure, the impact and high-frequency vibration between the pantograph collector strip, and the OCS mainly carried by the collector strip holder lead to metal fatigue or stress concentration, resulting in crack failure. Carbon strips are prone to fracture, shedding, and abnormal wear faults. As the only part of the HST in contact with the external power supply, the failure of carbon strips may lead to serious traffic safety accidents. In addition, the electrical system of the pantograph is prone to failure, which causes the inability of the pantograph to increase or decrease normally.

2.2 Traction transformer

Traction transformers, which are used to convert the 25 kV high-voltage electricity obtained from the OCS to the voltage required by the train, are important components of HSTs (Hugo et al., 2007; Dujic et al., 2012). CRH series EMUs generally use oil-immersed traction transformers, which mainly include the cooling device, transformer core, winding, and transformer oil. Taking the CRH2 EMU as an example, the EMU adopts the ATM9 traction transformer, which employs the single-phase shell type and the pressureless sealing method. Meanwhile, the transformer of ATM9 adopts the shell core, which is characterized in that the iron yoke surrounds not only the top and bottom of the winding but also the sides of the winding. The winding is the core part of the traction transformer, and the winding of ATM9 has the advantages of high electrical strength, good heat resistance, and high mechanical strength. The core components will inevitably experience fatigue degradation after long-term use of traction transformers, which will lead to different types of failures, such as transformer core, winding, and cooling device failures (Xiao et al., 2020). In addition, discharge and overheating faults are observed. Transformer overheating faults can be mainly divided into the following: Low temperature overheating (150°C–300°C), medium temperature overheating (300°C–700°C), and high temperature overheating (higher than 700°C). Overheating means that the temperature exceeds the allowable temperature for the normal operation of the transformer. If overheating is not immediately addressed, then the overheating fault will gradually develop from low to high temperature overheating, which will eventually seriously damage the transformer.

2.3 Traction converter

Traction converter is one of the key components of HSTs. This converter is installed at the bottom of the train, and its main function is to realize the conversion between alternating and direct currents (Drabek et al., 2010). Taking CRH2 EMU as an example, the EMU adopts the CI11 traction converter, which mainly comprises the pulse rectifier, intermediate DC circuit, traction inverter and AC contactor, traction control device, and cooling device. Inside the traction converter, the pulse rectifier converts the low-voltage single-phase AC from the traction transformer into DC; after passing through the intermediate DC circuit, the traction inverter converts it into three-phase AC for driving the traction motor. This converter controls the starting, braking, and speed regulations of the traction motor through voltage and frequency regulations. The abovementioned equipment is integrated into a box with a compact structure. A traction converter is installed on each power car to drive four parallel traction motors. Traction converter is a complex circuit system dominated by digital circuits and often yields undervoltage, overvoltage, overload, and overheating faults (Wu et al., 2012; Chen et al., 2020b). The classification of faulty components mainly includes inverter, rectifier, cooling device, and traction control device. In particular, the components most prone to failure are the power semiconductor devices and their control circuits in the inverter. Thus, researchers have conducted extensive research on the reliability of insulated gate bipolar transistor (IGBT) and its fault diagnosis.

2.4 Traction motor

Traction motors are the power source for HSTs. The traction motor converts electrical into mechanical energy during its traction station to drive the HST. The traction motor will act as a generator during the braking state to realize the regenerative braking of the train (Popescu et al., 2018; Nategh et al., 2020). CRH series EMUs generally use three-phase squirrel-cage asynchronous motors, which mainly comprise stators, rotors, bearings, fans, and frames. The structure diagram of a certain type of motor is shown in Fig. 3. Taking the CRH2 EMU as an example, the EMU adopts the MT205 three-phase squirrel-cage asynchronous motor, and each power car is equipped with four traction motors. The rated power of the motor is 300 kW, and the maximum speed is 6120 r/min. The traction motor adopts the bogie frame suspension method and is cooled by mechanical ventilation. Traction motors also have speed, current, and temperature sensors, which can be used to monitor the operation of the traction motor. However, these sensors are also fault-prone components in practice. Internal faults of traction motors primarily include stator, rotor, and bearing faults (Zhang et al., 2021b). The stator fault is mainly manifested as inter-turn and phase-to-phase short circuits. Rotor faults are demonstrated as broken rotor bar faults. Air gap eccentricity faults are also common faults in traction motors. Traction motor bearings primarily comprise cages, rolling elements, and outer and inner rings. The bearings are prone to failure because they are subjected to large alternating loads. The fault types of bearings can be mainly divided into inner ring, outer ring, and rolling element faults. The vibration of the motor will be strengthened and a large noise will be emitted under bearing faults.

3 Traction system fault diagnosis

The research and application of machine learning in traction system fault diagnosis are systematically reviewed in this section. The health status monitoring of the core components of the traction system, such as the pantograph, traction transformer, traction converter, and traction motor, is comprehensively discussed and analyzed. Deep learning is recognized as one of the main branches of machine learning. Moreover, deep learning is the most rapidly developing branch of machine learning, which has made breakthroughs in numerous fields. First, in addition to deep learning, the traditional fault diagnosis methods based on data-driven and machine learning algorithms are introduced. Then, the fault diagnosis models based on deep learning are comprehensively discussed. Finally, the fault diagnosis methods of the core components of the traction system are described separately.

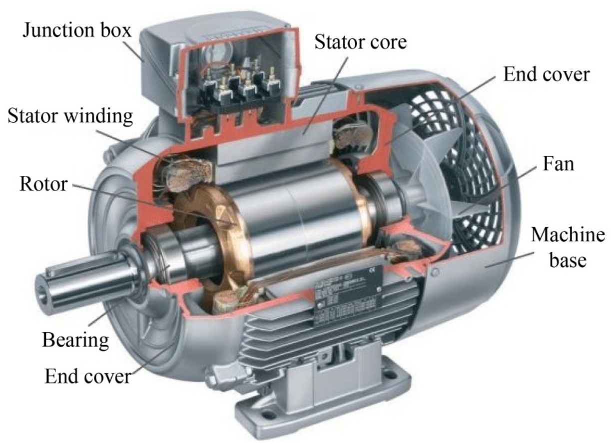

Fig. 3 Schematic of the structure of the traction motor.

3.1 Traction system fault diagnosis based on traditional data-driven methods

Hundreds of sensors are installed on HSTs to monitor their running status to collect train-related data continuously. For various monitoring objects, different valuable data, such as vibration, temperature, current and voltage, and sound signals, are collected. Artificial feature extraction is a crucial step in the traditional machine learning-based equipment fault diagnosis framework. For artificial feature extraction, experienced experts generally design corresponding feature extraction algorithms according to the characteristics of the monitored objects to extract features that can reflect the operating status of the equipment from the dataset. Different feature extraction algorithms may lead to extensively different final diagnosis results. Therefore, this step is heavily influenced by the bias of experts and the quality of the extracted features. Finally, the health status recognition aims to use traditional machine learning algorithms to establish the mapping relationship between the extracted features and the health status. Common traditional machine learning algorithms mainly include SVM, ANN, and *K*-nearest neighbor.

For feature extraction methods, Cao et al. (2014) used the Hilbert transform to remove interference information from the current signal and then employed wavelet packet energy (WPE) analysis to obtain fault-related information. Sun et al. (2017) used ensemble empirical mode decomposition (EEMD) to reduce the nonstationarity and local noise of the acquired signal to improve the performance of the diagnostic model. Sakaidani and Kondo (2018) used principle component analysis to reduce data dimensionality to remove redundant information while retaining valuable information. Octave band analysis is then performed to process the dimensionally reduced data to extract fault-related information. Zou et al. (2021) transformed the acquired vibration signals into the time-frequency maps through discrete wavelet transform (DWT) to highlight the frequency domain characteristics. For the fault diagnosis classifier, Peng et al. (2020b) proposed a probabilistic finite-state automata algorithm to diagnose bearing, air gap eccentricity, inter-turn short circuit, and bar broken faults of traction motors. Li (2022) studied machine learning and wavelet analysis algorithms and explored their application in traction motor fault diagnosis, then found that these algorithms achieved excellent diagnostic results. Xian et al. (2021) studied machine learning algorithms, such as SVM, ANN, and random forest, and explored their performance on anomaly detection, single-label multiclass fault diagnosis, and multilabel multiclass fault diagnosis. Finally, the suitability of machine learning algorithms for traction motor fault diagnosis in different situations was summarized.

3.2 Traction system fault diagnosis based on deep learning

The scale of the collected data has become increasingly large with the increase of the operating scale of HSTs and the development of data acquisition and storage hardware. The fault diagnosis framework based on traditional machine learning algorithms increasingly fails to meet the needs of large-scale data processing. Benefiting from the substantial improvement of computer hardware performance, especially the rapid development of GPU parallel computing, deep learning has achieved a series of breakthroughs and demonstrated unparalleled advantages in large-scale data processing. Deep learning algorithms can automatically obtain valuable information from large-scale data and learn mapping functions in high-dimensional space to diagnose the health status of equipment accurately. Deep learning frees researchers from tedious feature engineering through an end-to-end auto-diagnosis architecture in the context of intensifying amounts of data. This phenomenon has led to the rapid development of deep learning in the field of mechanical fault diagnosis, resulting in a series of achievements. For example, Shao et al. (2017) proposed a deep autoencoder network for locomotive gearbox fault diagnosis, which uses maximum correntropy to improve the loss function, thereby enhancing the learning capability of the model. For the processing of multisource and multisensor information, Ma et al. (2018) introduced a deeply coupled model based on the autoencoder, which can effectively perceive the interdependence between multisensor information to achieve accurate fault diagnosis. Considering CNN and long short-term memory (LSTM) as classical and effective depth models, a large number of interesting and effective fault diagnosis algorithms based on them have been developed. Wang et al. (2020a) introduced an attention mechanism considering bearing fault-related features to develop a CNN-based diagnostic framework and obtained satisfactory results. Chen et al. (2021) proposed a hybrid model that first uses CNN to learn features from the raw signal and then utilizes LSTM to achieve fault classification to integrate the advantages of CNN and LSTM.

Similarly, deep learning algorithms have gained the attention of researchers for traction system fault diagnosis. For example, Karaduman and Akin (2020) proposed a CNN-based framework for surface wear detection of current collector strips, which has excellent performance on real HST pantograph image datasets. Luo et al. (2019) used Fast-RCNN to detect pantograph faults, which had remarkably high accuracy for pantograph arc fault detection. Qin et al. (2019) used resolved gas analysis and a CNN-based fault diagnosis model for transformer health monitoring and employed vibration signals to locate transformer faults. Shao et al. (2020) proposed a motor fault diagnosis algorithm based on multisensor signals and CNN, proving that the multisensor model has superior stability and diagnostic performance. Xu et al. (2021b) used the stacked denoising autoencoder for fault diagnosis of traction motor bearings. Experiments showed that this method can obtain valuable fault features under variable working conditions and is superior to traditional fault diagnosis methods.

3.3 Fault diagnosis of key components of traction systems

3.3.1 Pantograph fault diagnosis

The fault diagnosis of the pantograph is mainly used to analyze its voltage and current signals, vibration signals, and image data to determine various possible fault conditions. Table 1 summarizes the research on pantograph fault diagnosis in recent years. For the current and voltage signals, this approach is mainly used to detect the pantograph arc to reduce the damage of the pantograph and catenary system. For example, Karakose et al. (2018) proposed a pantograph arc detection method based on signal processing and S-transform; meanwhile, Li et al. (2020) used the gray wolf optimization algorithm and SVM to identify the pantograph arc quickly and accurately. For vibration signal, the approach is mainly used to detect mechanical structure faults of pantograph, such as crack faults of pantograph core component. Shi et al. (2020) used the vibration signal to detect the horn crack and head bracket crack faults of the pantograph. They used EEMD to break down the vibration signal and SVM for fault diagnosis. Phala et al. (2021) utilized vibration signals and temperature data to detect anomalies in pantographs, thereby providing early warning of abnormal behavior. With the development of computer vision, an increasing number of researchers have adopted image data to detect the health status of pantographs. The image-based method can quickly analyze the important components of the pantograph to determine various fault conditions, such as pantograph slide plate faults, pantograph cracks, and pantograph arcs. Karaduman et al. (2017) captured the image data of the pantograph during its operation through a camera and then used a CNN-based method to detect the pantograph arc. Wei et al. (2020) proposed a neural network model for pantograph defect detection to realize pantograph slider defect recognition. Liu et al. (2019b) introduced a dropper fault detection method combining depthwise separable convolution and object detection network, which has high recognition accuracy. Lin et al. (2020) utilized the YOLO (you only

Table 1 List of research work on pantograph fault diagnosis

Reference	Method	Data	Application
Li et al. (2020)	Gray wolf algorithm, SVM	Current data	Pantograph arc detection
Shi et al. (2020)	SVM, EEMD, Particle swarm algorithm	Vibration data	Pantograph fault diagnosis
Karakose et al. (2018)	Fuzzy system, S-transform	Current data	Pantograph arc detection
Karaduman and Akin (2022)	Fuzzy classifier, Wavelet decomposition, Hough transform	Image data, Temperature data	Pantograph fault diagnosis
Aydin et al. (2014)	S-transform, Particle swarm algorithm	Video data	Pantograph anomaly detection
Phala et al. (2021)	SVM, *K*-means model	Vibration data, Temperature data	Pantograph anomaly detection
Aydin et al. (2015)	Gaussian mixture model, S-transform	Voltage and current data	Irregular positioning of the contact wire, Pantograph arc detection
Lu et al. (2021)	Multiview analysis, Subpixel edge detection algorithm	Image data	Slide surface wear monitoring, Defect location
Qu et al. (2019)	Genetic algorithm, Deep neural network	Height, stagger and hard point of contact line; Voltage; Contact force	Comprehensive pantograph and catenary monitor
Karaduman and Akin (2020)	Hough transform, Power law transform, CNN	Image data	Current collector strip surface defect detection
Tastimur et al. (2021)	Histogram equalization, CNN	Image data	Current collector strip surface wear monitoring
Shen et al. (2018)	CNN	Image data	Pantograph horn detection, Pantograph defect detection
Zhang et al. (2020b)	Deep pantograph detection network, Deep pantograph segmentation network, Edge detection, Hough transform	Image data	Contact point detection of pantograph and the catenary
Huang et al. (2019)	CNN	Image data, Video data	Pantograph arc detection and recognition
Lin et al. (2020)	CNN, YOLO v3	Image data, Video data	Pantograph electrical fault identification
Wei et al. (2020)	Pantograph defect detection neural network	Image data	Pantograph slide defect detection
Karaduman et al. (2017)	CNN	Image data	Pantograph arc detection
Luo et al. (2019)	Fast-RCNN	Image data	Pantograph anomaly detection
Liu et al. (2019b)	Depthwise separable convolution, Object detection network, Fault recognition network	Image data, Video data	Pantograph dropper fault detection
Wang et al. (2020b)	Salient segmentation, Generative adversarial networks	Image data	Pantograph anomaly detection
Sun et al. (2020)	Unsupervised learning, Superpixel segmentation	Video data	Pantograph state detection
Jiao et al. (2021)	CNN, Lightweight MobileNet, Feature pyramid network	Image data	Pantograph real-time detection
Huang et al. (2020)	CNN, Multi-information fusion	Visible light image, Infrared light image	Pantograph arc detection and recognition
Li and Wei (2018)	CNN	Image data	Pantograph slide defect detection
Na et al. (2020)	Image processing and deep learning	Image data	Detecting deformation on pantograph contact strip
Jiang et al. (2019)	Fast-RCNN	Image data	Defect detection of pantograph slider

look once) v3 algorithm to process and analyze pantograph images to identify pantograph electrical faults. In addition, researchers (e.g., Huang et al. (2020)) attempted to use visible and infrared light image fusion technologies to detect pantograph arc faults accurately.

3.3.2 Traction transformer fault diagnosis

Most research on fault diagnosis of traction transformers is based on dissolved gases analysis. The dissolved gases of the transformer are mainly derived from the following aspects. Most transformers use insulating oil and paper as insulating materials. The transformer works for a long time; thus, these insulating oil and papers will experience fatigue degradation after being subjected to drastic changes in the working environment and temperature. The aging decomposition of insulating oil and paper will generate a small amount of gas and dissolve in the insulating oil. Therefore, the analysis of these dissolved gases can quickly determine the health status of the transformer. Table 2 summarizes the research on traction transformer fault diagnosis in recent years. Bacha et al. (2012) proposed a transformer fault diagnosis model based on SVM and resolved gases analysis, which can realize the diagnosis of six kinds of transformer fault conditions. Dai et al. (2017) analyzed the interrelation of dissolved gas and fault categories and then proposed a deep belief network-based transformer fault diagnosis method, which

Table 2 List of research work on traction transformer fault diagnosis

Reference	Method	Data	Application
Dai et al. (2016)	Kernel principal component analysis, Random forest	Dissolved gases analysis	Traction transformer fault diagnosis
Zhu et al. (2015)	Radial basis function neural network, Fuzzy C-means algorithm	Dissolved gases analysis	Traction transformer early fault detection
Bi et al. (2020)	Variable weight coefficient, Bayesian network	Historical statistical data	Traction transformer condition monitoring
Zhou et al. (2021a)	Multiclass least-squares SVM, Differential evolution algorithm, Quadratic interpolation method	Frequency-domain dielectric spectrum test	Traction transformer insulation paper condition monitoring
Li et al. (2013)	Empirical mode decomposition, Energy weight, Information entropy	Differential current signal, Magnetizing inrush	Traction transformer fault diagnosis
Wan et al. (2009)	Improved fuzzy cellular neural network	Dissolved gases analysis, Water in oil, Key device resistance and electric current	Traction transformer fault diagnosis
Zhu et al. (2021)	Kernel principal component analysis, Fuzzy clustering	Dissolved gases analysis	Traction transformer condition monitoring
Xiao et al. (2020)	Bayesian network	Insulation resistance, Dielectric loss tangent value, Oil and gas, Power frequency voltage, Leakage current	Traction transformer fault diagnosis
Zhu et al. (2014)	Wavelet neural network, Hybrid particle swarm algorithm	Chromatographic data and electrical test data	Traction transformer fault diagnosis
MehdipourPicha et al. (2019)	Deep neural network	Dissolved gases analysis	Transformer fault diagnosis
Zhang et al. (1996)	ANN	Dissolved gases analysis	Transformer fault diagnosis
Zhang et al. (2020a)	Deep belief networks, Stacked denoising autoencoders, Relevance vector machines	Transformer vibration signal	Transformer fault diagnosis
Bacha et al. (2012)	SVM	Dissolved gases analysis	Transformer fault diagnosis
Wang et al. (2016)	Back propagation (BP) network, Continuous sparse autoencoder	Dissolved gases analysis	Transformer fault diagnosis
Li et al. (2016)	SVM, Genetic algorithm	Dissolved gases analysis	Transformer fault diagnosis
Seifeddine et al. (2012)	ANN	Dissolved gases analysis	Transformer fault diagnosis
Dai et al. (2017)	Deep belief network	Dissolved gases analysis	Transformer fault diagnosis
Zeng et al. (2019)	Hybrid grey wolf optimizer, Least square SVM	Dissolved gases analysis	Transformer fault diagnosis
Yuan et al. (2019)	Restricted Boltzmann machines, SVM	Dissolved gases analysis	Transformer fault diagnosis
Zhou et al. (2021b)	Gray wolf optimizer, Probabilistic neural network	Dissolved gases analysis	Transformer fault diagnosis
Li et al. (2021c)	Decision tree, Fully connected neural network	Frequency response analysis	Transformer windings fault diagnosis
Li et al. (2021a)	Hybrid kernel extreme learning machine, Gray wolf optimization algorithm, Differential evolution algorithm	Dissolved gases analysis	Transformer fault diagnosis
Liu et al. (2019a)	SVM	Frequency response analysis	Transformer winding deformation fault diagnosis
Song et al. (2018)	LSTM network	Transformer-condition-related data	Transformer operating state prediction and fault warning
Lin et al. (2018)	Deep belief network, LSTM network	Dissolved gases analysis	Transformer operating state prediction and fault warning
Qin et al. (2019)	CNN	Dissolved gases analysis, Vibration signal	Transformer fault diagnosis and location
Wang et al. (2018)	Stacking denoising autoencoder	Self-powered radio-frequency identification sensor	Transformer fault diagnosis
Zollanvari et al. (2021)	LSTM, Gated recurrent units	Vibration signal	Transformer fault diagnosis
Liao et al. (2021)	Graph convolutional network	Dissolved gases analysis	Transformer fault diagnosis

can substantially improve fault diagnosis accuracy. Lin et al. (2018) proposed a transformer operating state prediction model based on LSTM and deep belief network, which used LSTM to predict the changing trend of dissolved gas, and employed deep belief network to diagnose fault categories of transformers. Liao et al. (2021) introduced a graph convolutional network-based transformer fault diagnosis method, which utilizes graph convolution to model the complex nonlinear relationship between dissolved gases and fault types, resulting in excellent performance. In addition to the dissolved gas analysis, the researchers also attempted to use other information to diagnose transformer faults. Xiao et al. (2020) considered the correlation of factors, such as insulation resistance, dielectric loss tangent value, oil and gas, power frequency voltage, and leakage current, with transformer fault categories and proposed a fault diagnosis method based on the Bayesian network. Liu et al. (2019a) and Li et al. (2021a) realized transformer fault diagnosis using frequency response analysis and fault classifier, respectively. In addition, vibration signals are used for transformer health monitoring. Zollanvari et al. (2021) proposed a fault diagnosis model based on vibration signals and recurrent neural networks, which can diagnose transformer underexcitation and overexcitation faults.

3.3.3 Traction converter fault diagnosis

Traction converter is an important device for train energy conversion and may have various failure modes during operation. Most studies determine the health state of the traction converter by analyzing the current signal of it. Table 3 summarizes the research on traction converter fault diagnosis in recent years. Wu et al. (2012) used wavelet transform to process the current signal to obtain valuable features and then employed SVM to identify the fault condition of the traction converter. Zhao et al. (2014) used particle swarm optimization and genetic algorithm methods to optimize the parameters of SVM to improve the SVM-based classifier, thus achieving superior fault diagnosis performance of traction converters. Zhang et al. (2019) studied the remaining useful life (RUL) prediction of traction converters of CRH2 EMUs and proposed an RUL prediction model based on restricted Boltzmann machines and Bayesian network. The experiments proved that the model has excellent performance. Dong et al. (2021) used a multisensor signal fusion method for fault diagnosis of traction converters, which used 10 sensor signals and constructed an LSTM model for feature learning to make accurate predictions. In addition, sensors are the key to obtaining accurate train operation information. However, the performance degradation and failure of the sensor are also inevitable, which leads to the acquisition of erroneous information, thus threatening the driving safety. Chen et al. (2020b) studied the sensor fault diagnosis of traction converters and proposed a sensor fault diagnosis method based on signal processing technology and Bayesian network. Experiments showed

Table 3 List of research work on traction converter fault diagnosis

Reference	Method	Data	Application
Dong et al. (2021)	LSTM network	Temperature, voltage, current, and power signals; Multisensor information	Traction converter fault diagnosis
Zhao et al. (2014)	Particle swarm optimization, Genetic algorithm, SVM	Current signal	Traction converter fault diagnosis
Chen et al. (2020b)	Bayesian network, Short-time Fourier transformation, Principal component analysis	Current signal	Traction converter current sensor fault diagnosis
Wu et al. (2012)	Wavelet transform, SVM	Current signal	Traction converter fault diagnosis
Xia et al. (2018a)	Random vector functional network	Voltage and current signals	IGBT fault diagnosis
Hu et al. (2016)	Wavelet entropy	Voltage and current signals	Traction inverter open switch fault diagnosis
Zhang et al. (2019)	Bayesian network, Restricted Boltzmann machines	Upper/Lower voltage in the DC-link circuit	RUL prediction of traction converter
Xia et al. (2020)	Fast Fourier transform, Extreme learning machine, Random vector functional link network, Hybrid ensemble learning scheme	Current signal	IGBT open-circuit fault diagnosis
Gou et al. (2020)	Fast Fourier transform, Random vector functional link network	Current signal	IGBT and current sensor fault diagnosis
Cherif et al. (2020)	Complete empirical ensemble mode decomposition, Hilbert–Huang transform, ANN	Current signal	IGBT open-circuit fault diagnosis
Xia et al. (2018b)	Extreme learning machine, Ensemble classifier structure	Current signal	IGBT open-circuit fault diagnosis
Wang et al. (2019)	CNN, K-gray	Current signal	IGBT open-circuit fault diagnosis
Xia and Xu (2021)	Extreme learning machine, Transferrable data-driven fault diagnosis	Current signal	IGBT open-circuit fault diagnosis
Ke et al. (2020)	SVM, Genetic algorithm	Current signal	IGBT open-circuit fault diagnosis
Long et al. (2020)	Empirical mode decomposition, Statistical analysis, Generalized discriminant analysis, BP neural network	Current signal	IGBT open-circuit fault diagnosis
Wang et al. (2021)	Compressed sensing, CNN	Current signal	IGBT open-circuit fault diagnosis
Hu et al. (2020)	Independent component analysis, Neural network	Voltage and current signals	IGBT open-circuit fault diagnosis
Kou et al. (2020a)	Wavelet transform, Deep feedforward network	Voltage and current signals	IGBT open-circuit fault diagnosis
Kou et al. (2020b)	Deep feedforward network classifier	Current signal	IGBT open-circuit fault diagnosis
Guo et al. (2022)	Chirp mode decomposition and temporal convolutional network	Current signal	Modular multilevel converter fault diagnosis
Sarita et al. (2021)	Wavelet packets, SVM	Current signal	IGBT open-circuit fault diagnosis

that this method can quickly and effectively identify sensor faults. Gou et al. (2020) processed the current signal using fast Fourier transform to extract valuable spectral features and then used a random vector functional link network to learn from historical data to diagnose inverter current sensor failures.

Traction converters are the core components of HSTs, and IGBTs are the core components of traction converters. IGBTs are the weakest components in the traction converter and are remarkably prone to failure. The output current of the converter is distorted under the open-circuit fault of IGBTs, which may damage the traction motor and other components. Therefore, many scholars have investigated the open-circuit fault diagnosis of IGBTs and provided outstanding achievements. Xia et al. (2018b) proposed an IGBT open-circuit fault diagnosis model based on extreme learning machine, which effectively improved the diagnostic performance of the model through multiclassifier ensemble. Wang et al. (2019) proposed a conversion method of current signal to image data and then used a CNN to learn valuable fault features to diagnose IGBT open-circuit faults accurately. Wang et al. (2021) proposed a data-driven IGBT open-circuit fault detection and diagnosis method based on compressed sensing and CNN, which effectively improved the computational efficiency of the diagnosis model. Guo et al. (2022) used adaptive chirp mode decomposition to extract fault features of current signals and then proposed a fault diagnosis framework based on temporal convolutional network for IGBT open-circuit fault diagnosis.

3.3.4 Traction motor fault diagnosis

The condition monitoring of traction motor normally uses acceleration sensor, temperature sensor, acoustic emission, and current transformer to obtain the vibration, temperature, sound, and current and voltage signals of the motor. These signals contain characteristics that reflect the state of health of the traction motor. Vibration and sound signals are generally suitable for the fault diagnosis of traction motor bearings because traction motor bearings will produce regular vibration and large noise upon failure. The current and voltage signals are suitable for fault diagnosis of the traction motor rotor and stator. The current of the motor will be abnormal when the traction motor rotor and stator are faulty. In addition, the researchers found that the information of different sensor signals is complementary, and the diagnostic model can obtain higher performance using multisource information fusion technology than using a single sensor.

Table 4 summarizes the research on traction motor fault diagnosis in recent years. For example, Moosavi

Table 4 List of research work on traction motor fault diagnosis

Reference	Method	Data	Application
Zhang et al. (2021b)	Faster adaptive parameter multiscale dictionary learning method	Simulation and industrial data, Vibration signal	Traction motor rolling bearing fault diagnosis
Khamidov and Grishchenko (2021)	ANN	Current and vibration signals	Locomotive asynchronous traction motor fault detection
Moosavi et al. (2012a)	ANN	Current and voltage signals	Three-phase traction motor fault detection
Yetis et al. (2019)	ANN, SVM	Vibration signal	Early fault diagnosis of traction motor bearing
Moosavi et al. (2012b)	ANN	Current and voltage signals	Traction motors condition monitoring
Xu et al. (2021a)	WPD, CNN	Acoustic emission and vibration acceleration signals	Fault diagnosis of subway traction motor bearing (variable working conditions)
Li (2022)	WPD, SVM	Electromagnetic torque, speed, and six-phase current signals	Traction motor fault diagnosis
Peng et al. (2020b)	Probabilistic finite state automata, D-Markov machine	Current and voltage signals	Traction motor fault diagnosis
Xu et al. (2021b)	Stacked denoising autoencoder	Vibration signal	Subway traction motor bearing fault diagnosis
Sakaidani and Kondo (2018)	Octave band analysis, Machine learning	Leakage current signal	Traction motor bearing fault diagnosis
Sun et al. (2017)	EEMD, SVM	Current and voltage signals, Speed signal	Traction motor sensor fault diagnosis
Cao et al. (2014)	Hilbert transform, WPE analysis	Current and voltage signals	EMU traction motor fault diagnosis
Tran et al. (2013)	Fourier–Bessel expansion, Generalized discriminant analysis, Relevance vector machine	Transient current signal	Traction motor bearing fault diagnosis
Ray et al. (2020)	DWT-based multiresolution analysis	Current signal	Brush fault analysis of DC traction locomotive
Zou et al. (2021)	DWT, Improved deep belief network	Vibration signal	Traction motor bearing fault diagnosis
Ding et al. (2010)	WPD, BP neural network	Vibration signal	Traction motor fault diagnosis
Cheng and Yao (2018)	Fuzzy theory, Neural network, SVM	Current and voltage signals	Traction motor fault diagnosis
Xian et al. (2021)	Random forest classification, SVM, Neural network classification	Vibration signal	Traction motor fault diagnosis

et al. (2012a; 2012b) proposed an ANN algorithm for unbalanced voltage fault diagnosis of traction motors, which demonstrates good performance under five kinds of loads, based on the current and voltage signals. Cao et al. (2014) proposed a diagnostic algorithm based on Hilbert transform and WPE analysis, which can be used for the detection of air gap eccentricity faults, broken rotor bars, and stator winding faults. Sun et al. (2017) proposed an intelligent algorithm for traction motor sensor fault detection, which uses EEMD to convert the data into intrinsic mode functions and utilizes the kernel SVM to diagnose the state of health after extracting valuable features. Zou et al. (2021) studied the vibration signal of traction motor and proposed an intelligent algorithm for fault diagnosis of traction motor bearing. Their algorithm first uses DWT to process the vibration signals into time-frequency maps and then utilizes the deep belief network to establish the mapping relationship between the input signal and the fault information. Experiments on the traction motor bearing fault dataset of HSTs demonstrated that the proposed method significantly outperforms traditional machine learning algorithms. Xu et al. (2021b) used stacked denoising autoencoder for fault diagnosis of traction motor bearings. They found that this method can obtain valuable fault features under variable working conditions and is superior to traditional fault diagnosis methods. Xu et al. (2021a) further studied the application of multivariate information fusion strategy in traction motor bearing fault diagnosis. This strategy first employs wavelet packet decomposition (WPD) to process the obtained vibration and sound signals. The feature-level fusion method is then used to retain valuable features. Finally, CNN is utilized to predict the fault of traction motor. Shao et al. (2020) proposed a motor fault diagnosis algorithm based on multisensor signals and CNN, which proved that the multisensor model has superior stability and diagnostic performance. Taking HST axle boxes, gearboxes, and traction motors as research objects, Gu and Huang (2020) explored the application of multitask deep learning on HSTs. The proposed method can identify bearing temperature anomalies in real time.

4 Challenges and prospects

Machine learning technology has made exemplary achievements in fault diagnosis of HST traction systems. However, most methods based on machine learning only consider the diagnosis and analysis of the key component of the traction system under simple working conditions. These methods rarely consider the critical problems encountered in the actual application process when designing machine learning algorithms. In addition, machine and deep learning models have the following shortcomings. These models are data-dependent and require massive amounts of training data to optimize the learnable parameters. The generalization performance of these models is insufficient, and addressing unseen cases or data is challenging. Significant gaps in the interpretability studies of these models are also observed. Therefore, the existing machine learning methods still have the following problems urgently requiring solutions.

4.1 Diagnosis and analysis under nonstationary conditions

In a steady-state (constant speed, constant load, and high signal-to-noise ratio), the distribution of fault features of sensor signals is relatively fixed, and machine learning technology can easily learn these fault information from historical data to obtain good diagnostic performance. However, in the actual operation of HSTs, the obtained sensor signals contain considerably complex signal components and various frequency components are mixed (Uma Maheswari and Umamaheswari, 2017), increasing the difficulty in learning useful fault feature information using machine learning methods. In addition, the characteristic distribution of the collected signals dynamically changes continuously due to the complex and varying operating conditions of HSTs. These changes increase the difficulty in accurately determining the decision boundary for machine learning algorithms, resulting in incorrect decisions made by the algorithm. Finally, the failure response is weak in the early stages of failure. These responses are easily overwhelmed by complex noise (Peng et al., 2020a), which poses a significant challenge to the feature learning capability of machine learning methods.

Future research can explore solutions to the above challenges from the following aspects.

(1) The influence of HST changing operating conditions on the collected signals can be explored. Combined with the research object and the characteristics of the signal itself, signal analysis techniques can be used to reduce the influence of operating conditions on the signal characteristics and highlight fault-related information.

(2) The influence of HST changing working conditions on the machine learning model can be explored and the transfer learning technology can be combined to propose a fault diagnosis model with domain-invariant feature learning capability. Therefore, the diagnosis model has excellent domain adaptability.

(3) The impact of environmental noise on machine learning models can also be explored and the advantages of traditional denoising algorithms can be combined to develop signal denoising models based on machine learning. Therefore, machine learning methods with good noise immunity and can effectively capture weak early fault features can be developed.

Transfer learning technology can be used to establish fault diagnosis models with domain-invariant feature learning capability for cross-domain diagnosis problems. Most transfer learning models aim to apply the knowledge obtained from a stationary working condition to the other (Zhong et al., 2019; Han et al., 2021a; Peng et al., 2021). Therefore, the diagnostic model can use data under known conditions to process data under unknown conditions, considerably improving the performance of the diagnostic model under nonstationary conditions. Obtaining data for all operating conditions is impractical. With the capability to process data of unknown working conditions, the diagnostic model has substantial application potential. However, the operating conditions are not only unknown but also nonstationary in practice. That is, the feature distribution of the data is constantly changing, thus complicating the application of transfer learning. Fortunately, researchers have explored this problem and proposed corresponding solutions. For example, Minku (2019) comprehensively discussed the application of transfer learning in nonstationary environments and studied and analyzed some typical methods. Du et al. (2020) proposed a novel multisource mapping approach with transfer learning for nonstationary environments (MARLINE). MARLINE can benefit from knowledge from multiple data sources in nonstationary environments even when the source and target concepts do not match.

4.2 Diagnosis and analysis under imperfect datasets

Under perfect data conditions (with a large amount of available and accurately labeled data), machine learning methods can maximize their excellent feature learning capabilities to obtain sufficient fault-related feature information from the data. However, running for a long time with faults is difficult for HSTs, and analyzing and determining the types of HST faults is also a remarkably time-consuming task. Therefore, creating large volumes of human-labeled data is expensive and labor-intensive. When only a small amount of labeled data is available, achieving acceptable diagnostic performance is difficult for data-driven algorithms (Li et al., 2021b). Therefore, obtaining sufficient fault-related features from a small amount of labeled data and learning valuable information from a large amount of easily obtained unlabeled data are urgent problems for data-driven methods. Furthermore, data-driven models are prone to fitting mislabeled data when labels are incorrect, leading to erroneous diagnostic decisions. This phenomenon is also a vital issue to be studied for data-driven methods (Song et al., 2022). In addition, the imbalance of data categories increases the difficulty in handling all fault categories comprehensively and accurately by diagnostic models. Therefore, “imperfect datasets” can be defined as datasets with limited labels, datasets with limited samples, imbalanced data, and datasets with incorrect labels.

Future research can explore solutions to the above challenges from the following aspects.

(1) Excellent ideas can be obtained from semi- and self-supervised learning paradigms to develop unsupervised or semi-supervised machine learning frameworks for fault diagnosis.

(2) Feature learning schemes with excellent robustness and generalization can be explored to improve the feature learning capability of data-driven models under considerably small amounts of data. In addition, the excellent achievements of few-shot learning can be borrowed to improve the performance of fault diagnosis methods in the case of insufficient data.

(3) The performance of data-driven methods on mislabeled datasets can be explored to analyze the reasons for the degradation of diagnostic model performance and machine learning algorithms that are robust to mislabeling can be proposed.

(4) Efficient data augmentation and data resampling methods can be investigated to improve the performance of diagnostic models on imbalanced datasets. Furthermore, efficient weighted loss functions are examined to avoid diagnostic models that ignore classes with small sample sizes.

4.3 Insufficient interpretability of diagnostic models

The powerful advantage of data-driven methods lies in their learning of valuable feature information from historical data by training complex neural network models. However, understanding the decision-making process inside the data-driven model is difficult (Zhang et al., 2021a). Especially for the fault diagnosis model based on deep learning, this process seriously lacks interpretability, which significantly limits the practical application potential of deep learning technology. The uninterpretability of deep learning models markedly reduces the reliability of the diagnostic models and may introduce a series of unpredictable security problems. Using an unexplainable diagnostic model to gain the trust of the staff introduces difficulties in the actual application process. If the model provides an incorrect diagnostic decision, then optimizing the model in a targeted manner is also difficult for researchers. Therefore, exploring the interpretability of deep learning to understand the feature learning and decision-making process inside the model thoroughly is of considerable importance.

Future research can explore solutions to the above challenges from the following aspects.

(1) The intrinsic connection between feature learning of deep learning and input data can be explored and in-depth deconstruction of the internal learning mechanism of diagnostic models can be performed for intuitive and reliable interpretability analysis.

(2) The inherent relationship between feature learning of deep learning and diagnostic decision-making can be investigated and the decision-making basis of the diagnostic model can be analyzed and discussed to provide a reasonable and credible analysis of the model’s decision logic and behavior boundaries.

5 Conclusions

The traction system is the core subsystem of HSTs, which plays a vital role in energy conversion and train driving. The traction system will inevitably degrade and cause various failures during the long-term operation of HSTs, thus threatening the safety of trains. Therefore, fault monitoring and diagnosis of the traction system of HSTs are necessary. First, this paper briefly introduces the structure and function of the core components of the HST traction system. Then, this paper provides a comprehensive overview of machine learning research in the field of traction system fault diagnosis. In addition, a detailed analysis of related studies on pantograph fault, traction transformer fault, traction converter fault, and traction motor fault diagnosis is provided. Finally, the challenges encountered by existing machine learning-based diagnostic models are explored and their prospects are analyzed. The authors of this article aim to provide a comprehensive reference for researchers in this field.

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