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Review

A Review of Fault Diagnosis Methods for Key Systems of the High-Speed Train

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Abstract: High-speed train is a large-scale electromechanical coupling equipment with a complex structure, where the coupling is interlaced between various system components, and the excitation sources are complex and diverse. Therefore, reliability has become the top priority for the safe operation of high-speed trains. As the operating mileage of high-speed trains increases, various key systems experience various degrees of performance degradation and damage failures. Moreover, it is accompanied by the influence of external environmental high interference noise and weak early fault information. Thus, those factors are serious challenges for the condition monitoring and fault diagnosis of high-speed trains. Therefore, this paper summarizes the research progress and theoretical results of the fault detection, fault isolation, and fault diagnosis methods of the key systems of high-speed trains. Finally, the paper summarizes the applicability of the main methods, discusses the challenges and opportunities of condition monitoring and fault diagnosis of high-speed trains, and looks forward to improving its diagnosis level.

Keywords: high-speed train; key systems; fault diagnosis; feature extraction; pattern recognition

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1. Introduction

With the advantages of high speed, large carrying capacity, safety, and all-weather operation, high-speed trains have become one of the most popular modern means of transportation. With the development of high-speed trains toward high speed and electrification, as well as the long operating mileage, higher requirements have been proposed for their safety and stability. Due to the long-running in various bad environments and with uncertain factors, some system components of the high-speed train will inevitably break down, even suffering serious failure [1]. If these faults are not discovered and handled in time, they eventually lead to disastrous consequences. A series of train accidents in recent years show that effective condition monitoring and fault diagnosis technology can provide a reliable solution to prevent or reduce the occurrence of similar incidents in the future. Therefore, it is very urgent and necessary to study the condition monitoring and fault diagnosis of high-speed trains to improve the safety of the rail transit system [2,3].

In recent years, good research results have been achieved in fault condition monitoring and diagnosis technology for mechanical systems [4]. Therefore, drawing on existing technologies can provide certain theoretical support for condition monitoring and fault diagnosis of high-speed trains, which play an important role in maintaining the safety of railroad transportation systems. However, there are still some difficulties in fault diagnosis of high-speed trains. Firstly, the diverse service environment of high-speed trains, with large speed fluctuations and unclear shock loads, leads to signals with strong nonlinearity [5,6]. Secondly, the early fault information of each key system is weak, and the fault signal is easily disturbed by the background noise, leading to greater difficulty in early fault feature extraction. In addition, the relationship between the system components is extremely complex. Hence, the collected signals are not only independent but also have a certain correlation and often contain more interference components. To this end, this thesis summarizes the fault diagnosis techniques of key systems (bogie system, traction/braking system, and electrical/information control system) of high-speed trains in recent years, as shown in Figure 1. From Figure 1, signal processing, machine learning, and deep learning techniques are effective methods to achieve condition monitoring and fault diagnosis of each key system. Finally, the development of high-speed train fault diagnosis technology is forecasted. The main contributions of this study are as follows:

(1) The fault diagnosis methods of the bogie system of the high-speed train are presented.
(2) The fault diagnosis methods of the traction system and brake system of the high-speed train are summarized.
(3) The fault diagnosis methods of electric systems and information control systems of the high-speed train are overview.
(4) The applicability of main fault diagnosis methods for high-speed trains is discussed.

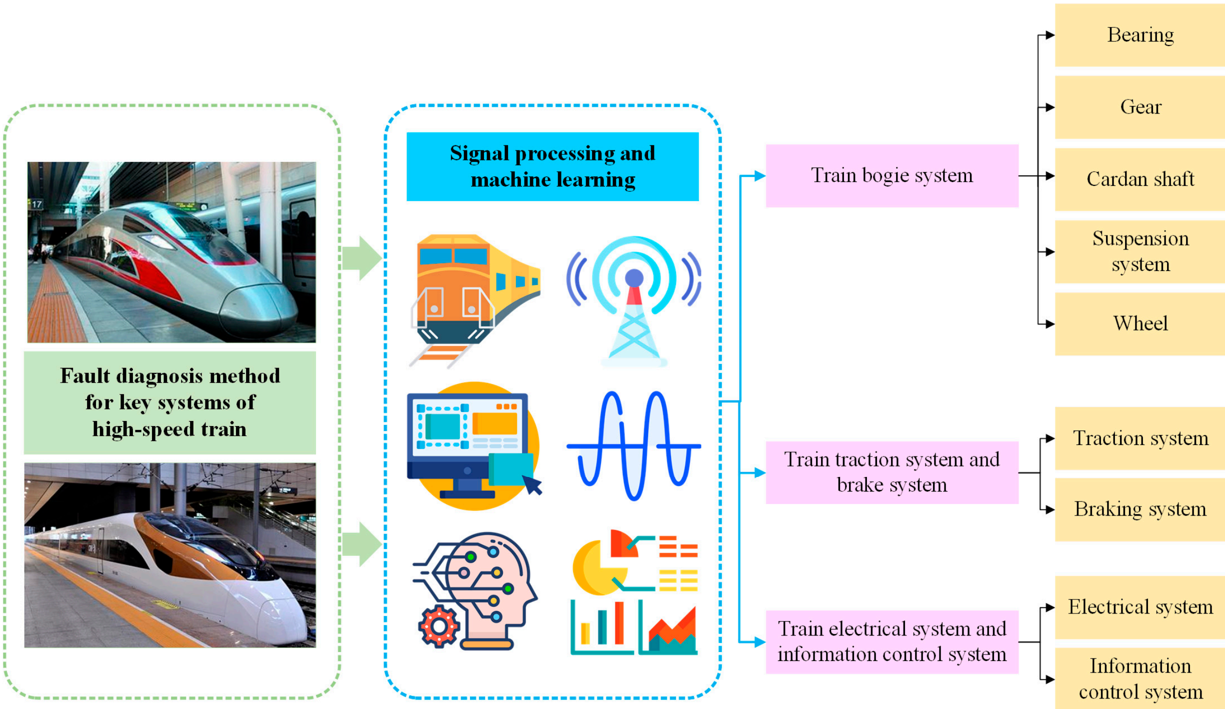

Figure 1. Fault diagnosis for key systems of high-speed trains.

2. Fault Diagnosis of High-Speed Train Bogie System

2.1. Fault Diagnosis of Train Bearing

Bearings are widely used in mechanical systems and are essential parts of high-speed trains. The bearings of trains work under heavy loads and alternating impact stresses for a long time and are highly susceptible to pitting, cracking, wear, and other failures. Their main diagnostic techniques are shown in Figure 2.

To address the challenge of the large data volume of high-speed trains, Liu et al. [7] proposed a method based on mapping approximate principal component analysis (PCA), and validated it with actual train operation data. To effectively analyze the vibration signals of bearings, Cao et al. [8] presented a method based on empirical wavelet transform (EWT) to effectively detect outer ring faults, rolling body faults, and composite faults of bearings. Due to the relative motion between the train and the detection system, the collected acoustic signal is distorted by the Doppler effect, so Zhang et al. [9] introduced the method of multi-scale chirp path pursuit (MSCPP) and variable digital filter (VDF) to effectively suppress the Doppler effect and extract the bearing fault features. Ding et al. [10] proposed a detection method based on shock response convolutional sparse coding, thus improving the accuracy of bearing fault detection. To extract bearing fault features effectively, Li et al. [11] proposed an acoustic detection technique based on a sparse decomposition of resonant signals and singular value decomposition, which is superior to traditional methods. To improve the diagnostic accuracy of train bearing faults, Li et al. [12] advanced a multiscale morphological filter method based on feature selection using maximum correlation based on more than 30 feature indicators of vibration signals. Through the technique of time domain interpolation resampling, Zhang et al. [13] proposed an enhanced spline kernelized wavelet transform-based acoustic detection method for roadside acoustics, which effectively overcomes the distortion caused by the Doppler effect. Ding et al. [14] introduced a sparse representation method based on cyclic structure dictionary learning and applied it to the extraction of bearing fault features of trains, and the effectiveness of the proposed method was verified by simulated signals and measured signals. Zhao et al. [15] presented an improved harmonic product spectrum (IHPS) to identify multiple modulation sources hidden in the vibration signal, which not only effectively identifies the fault features but also eliminates the influence of non-fault modulation on the fault features. Huang et al. [16] optimized the key parameters of variational mode decomposition (VMD) and proposed an improved scale-space VMD method, which can automatically decompose the resonance band of bearing signals and further reveal the fault mode. Through a time-frequency data fusion strategy, Zhang et al. [17] advanced a method of time-frequency distribution (TFD) that can effectively separate the acoustic signals in the time-frequency domain and achieve an accurate diagnosis of bearing faults. Minimum entropy deconvolution (MED) enhances the impulse component of the signal, and Cheng et al. [18] designed a particle swarm algorithm optimized MED method, and the experimental results showed that the method could effectively diagnose bearing faults with a low signal-to-noise ratio and outperforms other methods. Through the singular value decomposition package (SVDP) and reconstruction of the Hankel matrix, Huang et al. [19] proposed a method of extended SVDP (ESVDP) and validated it with the failure data of train bearings. References [20,21] improved the conventional signal processing method and were able to successfully identify train-bearing faults. In addition, the results of references [22–24] show that fault identification of train bearings can be achieved based on morphological component analysis, data-driven analysis, and improved SVDP. Furthermore, the time-frequency features of the empirical modal decomposition of the signal are input to a support vector machine, which can achieve fault diagnosis of train bearings [25–27]. To improve the accuracy of fault diagnosis across domains, Shen et al. [28] proposed an adaptive convolutional ResNet-50 network model and validated it with train bearings. Zhang et al. [29] proposed an effective adaptive Gabor sub-dictionary approach that can extract fault features from the vibration signals of trains. With the autoencoder as the feature learning model, bearing fault types can be accurately identified through the weighted voting strategy and generative adversarial network (GAN) [30,31]. Xu et al. [32] introduced a time-frequency domain feature extraction method based on sound signals and vibration signals and applied it to condition monitoring and service life prediction of train bearings.

Therefore, the bearing fault diagnosis method for high-speed trains is mainly achieved by fault feature extraction and fault pattern recognition. In feature extraction, the main methods are EWT, singular value decomposition, VDF, empirical modal decomposition, MED, wavelet transform, VMD, TFD, etc. In pattern recognition, the main methods used are principal component analysis, support vector machines, dictionary learning, self-encoders, generative adversarial networks, etc.

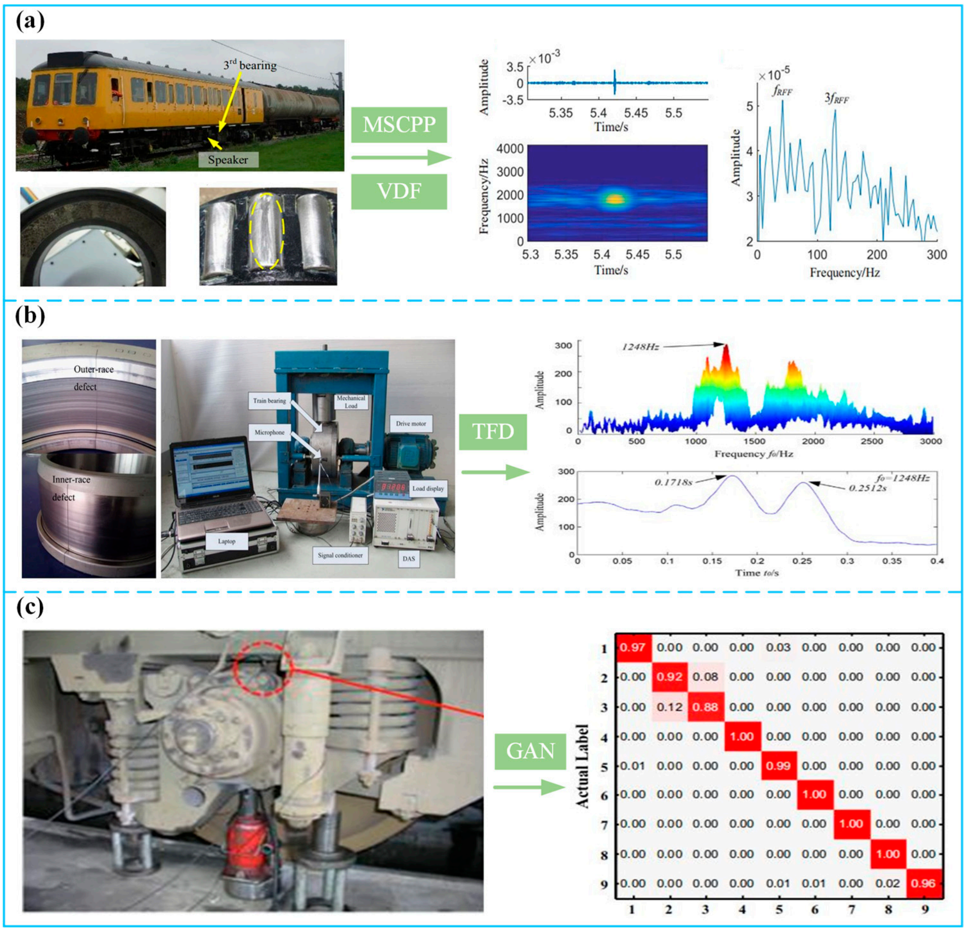

Figure 2. Fault diagnosis method of bearing: (**a**) multiscale chirp path pursuit (MSCPP) and variable digital filter (VDF) [9]; (**b**) time-frequency distribution (TFD) [17]; (**c**) generative adversarial network (GAN) [30].

2.2. Fault Diagnosis of Train Gear

Gears are an important part of high-speed train transmission systems, which usually work under harsh environmental conditions (such as sudden shock loads, unbalanced shaft conditions, heavy loads, large speed fluctuations, etc.), resulting in gears inevitably cracking, pitting, wearing, spalling, suffering tooth surface damage, etc. Their main diagnostic techniques are shown in Figure 3.

It is well known that gear failure is the main source of vibration and noise in high-speed trains. To effectively extract the fault features of train gears, Chen et al. [33] designed an improved complementary ensemble empirical mode decomposition (CEEMD), which not only reduces the problem of modal aliasing but also reduces the residual noise in signal reconstruction and obtains valuable intrinsic mode functions (IMFs). In order to detect the early failure of cracks in gears, Zhang et al. [34] proposed a time-frequency statistical feature (TFSF) method based on finite element analysis combined with modal analysis, which not only obtained the causes of crack generation but also effectively identified the different degrees of crack failure. To address the problem of weak extraction of weak fault features under strong background noise, Zhu et al. [35] presented an improved maximum correlated kurtosis deconvolution (MCKD) method, which can effectively diagnose multiple faults in train gears and outperforms some conventional methods. To extract fault information from the vibration signals of train gears, Wang et al. [36] advanced an improved empirical wavelet transform method based on EWT using the kurtosis index and inverse transformation technology and applied it to gear fault identification. Combining the advantages of spectral kurtosis and tunable Q-factor wavelet transform (TQWT), Long et al. [37] introduced an improved TQWT, which was verified by simulation signals and experimental signals of train gears. Zhu et al. [38] proposed a method based on singular value decomposition (SVD) and multipoint optimal minimum entropy deconvolution adjusted (MOMEDA) and applied it to the fault diagnosis of train gears. In order to reduce the degree of modal aliasing in empirical mode decomposition (EMD), Peng et al. [39] proposed a method based on a soft sieving criterion to optimize EMD and applied it to the simulated signals and the measured signals of train gear faults. Li et al. [40] developed a method to optimize VMD with a discrete difference evolutionary (DDE) algorithm, combined with MED for noise reduction, and successfully identified multiple faults in train gears.

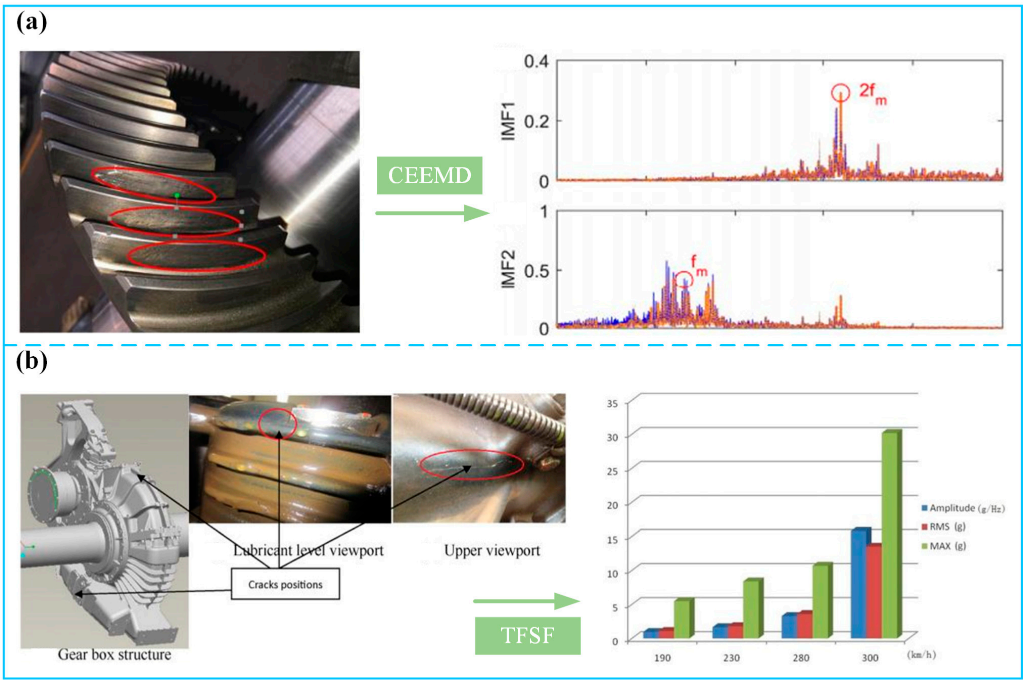

Figure 3. Fault diagnosis method of gearbox: (**a**) improved complementary ensemble empirical mode decomposition (CEEMD) [33]; (**b**) time-frequency statistical feature (TFSF) [34].

Therefore, gear fault diagnosis is mainly accomplished by fault feature extraction, and the main methods used include CEEMD, MCKD, wavelet transform, singular value decomposition, EMD, VMD, TFSF, etc.

2.3. Fault Diagnosis of Train Cardan Shaft

The cardan shaft is the key power transmission component of high-speed trains. It is connected to the drive motor and the gearbox through two universal joints, which transmit the traction force generated by the motor to the gearbox, and then drive the train forward. Additionally, it is a slender mechanical structure with little bending and stiffness, which makes it easy to appear to various degrees of deformation during the train's long run, causing abnormal vibration of other components, thus leading to damage. Since the cardan shaft not only needs to transmit traction power but also needs to coordinate complex motion relationships, its failure causes a major train accident. Their main diagnostic methods are displayed in Figure 4.

In order to quickly diagnose the misalignment fault of the cardan shaft of trains, Hu et al. [41] presented a method based on dual-tree complex wavelet packet transformation (DTCWPT), which greatly eliminated the interference of other mechanical noises in the vibration signal of the cardan shaft and was verified by train data. By using wavelet packet decomposition, Ding et al. [42] proposed a method based on double decomposition and double reconstruction (DDDR), which can effectively extract the fault features of the universal axis of the train and is better than wavelet decomposition and wavelet singular value decomposition. By using the Hamming window, Li et al. [43] designed a method based on an improved morphological filter that can effectively identify the characteristic frequencies and multiplicative information of train cardan shaft faults.

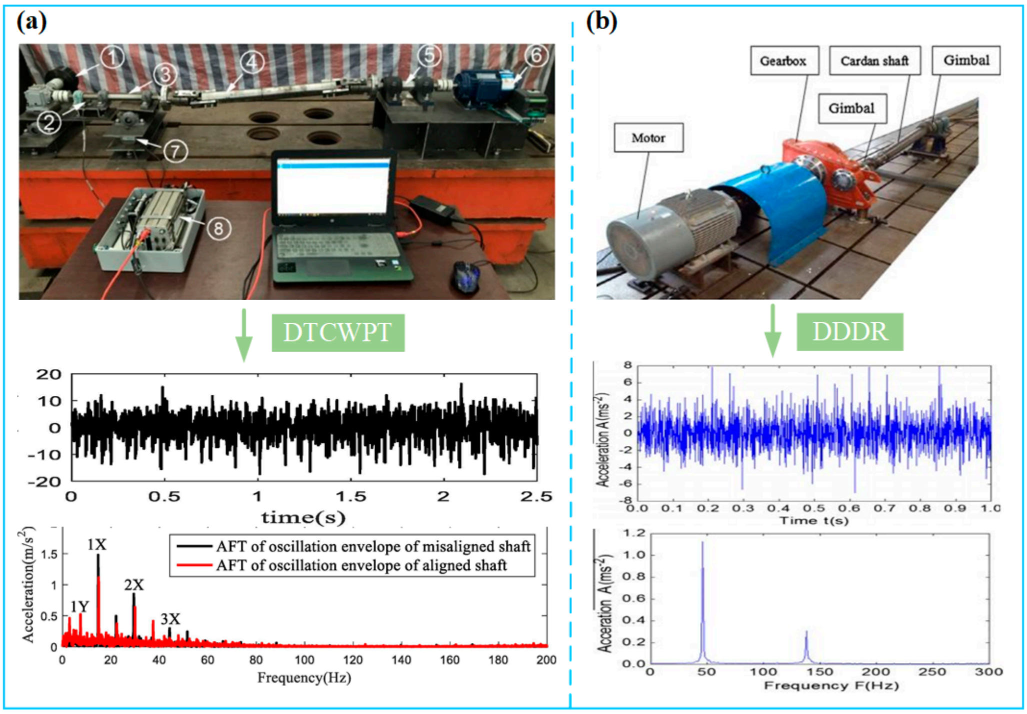

Figure 4. Fault diagnosis method of cardan shaft: (**a**) dual-tree complex wavelet packet transformation (DTCWPT) [41]; (**b**) double decomposition and double reconstruction (DDDR) [42].

Therefore, the fault diagnosis of the train cardan shaft is mainly made by fault feature extraction, and the main applied methods include wavelet packet transform, morphological filter, singular value decomposition, etc.

2.4. Fault Diagnosis of Train Suspension System

The suspension system is an important part of the high-speed train, which mainly consists of the frame, primary suspension, secondary suspension, drive unit, etc. The suspension system plays an important role in power transmission and load bearing, and its performance directly affects the train's running quality and safety. Their main diagnostic techniques are shown in Figure 5.

As the mileage of a high-speed train increases, its suspension system suffers from various types of fatigue damage and performance degradation, which increases the risk of train accidents. By taking advantage of the good extraction ability of deep learning, Zhang et al. [44] proposed a method based on a deep neural network (DNN) that can effectively identify multiple faults in a suspension system with an accuracy of 92.5%, which is better than traditional signal methods. To detect early faults in train suspension systems in a timely manner, Dumitriu et al. [45] calculated the correlation function of the vibration acceleration signals of a train under unbalanced forces and thus diagnosed the faults of the dampers. Due to the complex vibration signals and weak fault information of the train's suspension system, Gou et al. [46] presented a method based on VMD multiscale entropy combined with SVM and validated it with experiments. Based on the analysis of the vibration signal features of different components of the suspension system, Qin et al. [47] introduced a method based on the information entropy of the ensemble empirical modal decomposition to diagnose multiple fault types of the train suspension system effectively. Qin et al. [48] proposed a fault identification technique based on wavelet entropy features for typical faults in train suspension systems. Due to the strong noise and difficult feature extraction of the train suspension system, Guo et al. [49] proposed a method based on an ensemble deep belief network (EDBN) and combined it with SVM to achieve a diagnosis. In addition, the application of ensemble empirical mode decomposition (EEMD) entropy and wavelet packet energy with least squares support vector machines as classifiers can effectively identify faults in suspension systems [50,51]. To further improve the fault diagnosis accuracy of train suspension systems under small sample conditions, references [52,53] designed methods based on combined permutation entropy and EEMD permutation entropy, respectively. By using the time-frequency domain features of vibration signals and convolutional neural networks (CNN), Wu et al. [54] presented a multi-domain fusion (MDF)-based method to successfully diagnose faults such as air springs and transverse dampers of train suspension systems. Zhu et al. [55] advanced a feature extraction method based on energy entropy and singular entropy, and the effectiveness of the method was verified by simulated and measured signals of the train suspension system. Additionally, in order to improve the diagnostic accuracy of the suspension system, references [56,57] developed the dual-tree complex wavelet and singular value decomposition, respectively. Ye et al. [58] designed a method based on multiscale permutation entropy and linear local tangent space alignment (LLTSA), which was finally validated with tracking data of the suspension system of China's CRH3 high-speed trains. To detect early faults in high-speed train suspension systems as early as possible, Wu et al. [59] introduced a method based on improved ToMFIR, which was then validated with data from the Chinese CRH2 and was better than the conventional method. To address the problem of great difficulty in early fault diagnosis of the anti-yaw dampers of the suspension system of high-speed trains, Kaiser et al. [60] proposed a real-time monitoring method based on a nonlinear constraint model. To change the maintenance of train suspension systems from scheduled repair to condition repair, Zoljic et al. [61] proposed a method based on cubic Kalman filtering, which was verified experimentally. To improve the diagnostic accuracy and robustness of suspension systems for high-speed trains, Aravanis et al. [62] presented a method based on a functional model (FM), which was experimentally verified to have better performance compared to the traditional method.

Therefore, the fault diagnosis of the train's suspension system is mainly accomplished by feature extraction and pattern recognition. The main methods applied in feature extraction include permutation entropy, LLTSA, wavelet packet, VMD, MDF, FM, singular value decomposition, EEMD, etc. In pattern recognition, DNN, SVM, LSSVM, CNN, Kalman filters, etc., are mainly used.

2.5. Fault Diagnosis of Train Wheels

The wheels of high-speed trains are important components for carrying, guiding, traction, and braking. When the train is in normal service, due to the long-term interaction between the wheels and the track, it will have different degrees of wear and tear and even cracks, which affects the stability of the train. Therefore, in order to improve the safety and reliability of train operation, early failure of wheels (wear, cracks, etc.) should be detected as soon as possible, and maintenance should be carried out as soon as possible. Their main diagnostic techniques are shown in Figure 6.

To accurately identify defects in the wheels of high-speed trains, Skarlatos et al. [63] proposed a method based on fuzzy logic, which was experimentally shown to reduce the maintenance cost of trains. To be able to detect wheel defects in real time, Wang et al. [64] proposed a real-time detection method based on a Bayesian dynamic linear model, which can detect the degree of wheel damage and show the abnormal values. To obtain the effect of seasonal changes on wheels, Chi et al. [65] presented a method based on three Bayesian data-driven models with field monitoring data showing that the wear is more severe during the summer season than in other seasons. Due to the great difficulty of wheel fault detection in high-speed trains, Li et al. [66] advanced an algorithm of adaptive multiscale morphological filtering (AMMF) that can extract the wheel fault features in strong background noise. By establishing a wear model of the wheel, Zeng et al. [67] developed a physical data-driven approach to achieve accurate prediction of wheel performance degradation and effective assessment of the remaining service life. Chellaswamy et al. [68] designed a dynamic differential evolution algorithm to identify defects and compared it with the chaotic particle swarm algorithm and the genetic algorithm, and experimental results showed that the method is more effective. Liang et al. [69] introduced an adaptive noise canceling (ANC) method, and the experimental results showed that the method could effectively reduce noise interference and extract fault features from strong background noise. To accurately predict the early defects of wheels and reduce the maintenance time of railroad vehicles, Ward et al. [70] proposed a method to predict wheel wear. Lingamanaik et al. [71] collected signals and assessed wheel wear by installing various sensors (vibration acceleration, displacement, etc.) in the carriage, bogie, and wheelset. To identify fatigue cracks in high-speed train wheels more effectively, Zhou et al. [72] developed a method based on the energy entropy of EMD and the Elman neural network, which uses the energy entropy of EMD as a feature and the Elman as a classifier.

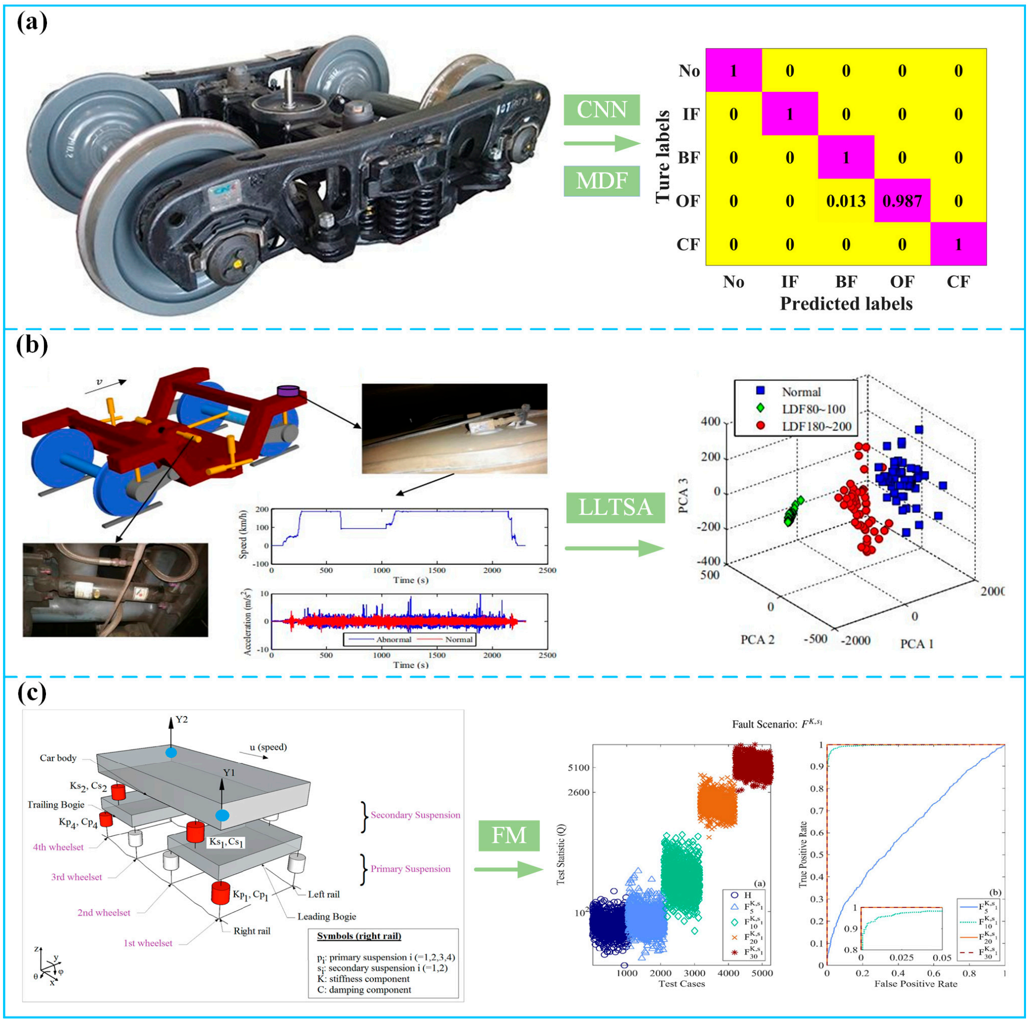

Figure 5. Fault diagnosis method of bogie suspension system: (**a**) multi-domain fusion (MDF)–convolutional neural network (CNN); (**b**) linear local tangent space alignment (LLTSA) [58]; (**c**) functional model (FM) [62].

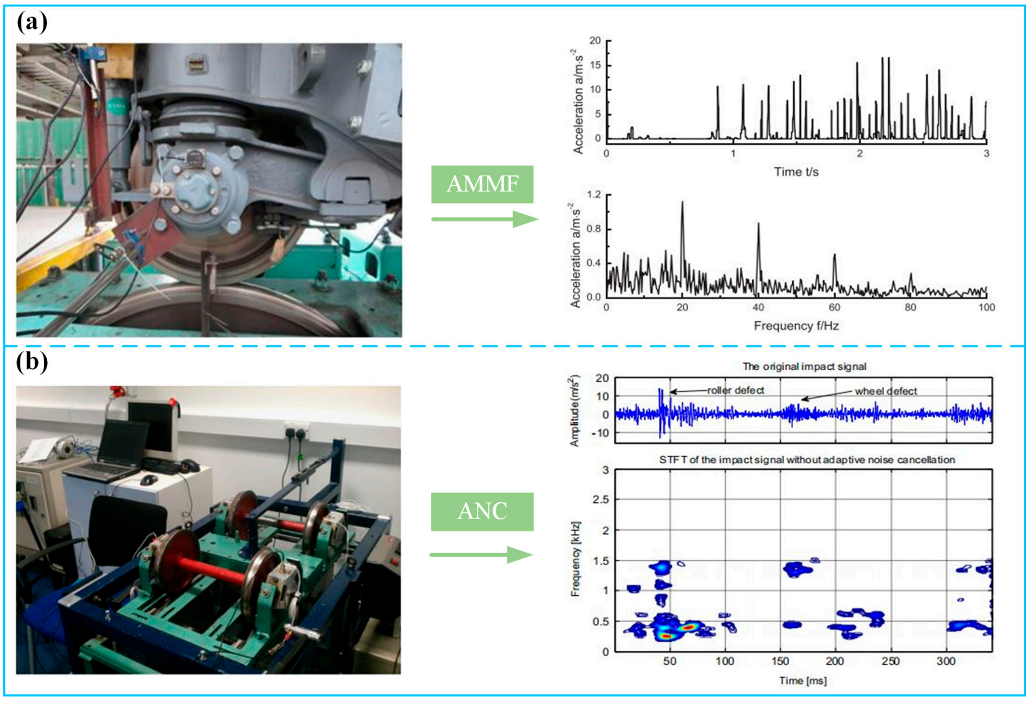

Figure 6. Fault diagnosis method of wheel-rail system: (**a**) adaptive multiscale morphological filtering (AMMF) [66]; (**b**) adaptive noise canceling (ANC) [69].

Therefore, the fault diagnosis of train wheels is mainly achieved by feature extraction and pattern recognition. In feature extraction, morphological filters, ANC, AMMF, EMD, and other methods are mainly applied. In pattern recognition, the main methods used include Bayesian and Elman neural networks, etc.

3. Fault Diagnosis of the High-Speed Train Traction System and Brake System

3.1. Fault Diagnosis of Train Traction System

As the heart of the whole high-speed train, the traction system of the train can generate traction power, which mainly consists of a traction transformer, traction power supply (rectifier, DC link, and inverter), and traction motor. Early failures of traction systems are often caused by unavoidable factors, such as the degradation of winding insulation and the aging of mechanical and electronic components, which in turn affect the safety of trains. Therefore, these early faults need to be detected in time, and their main diagnostic techniques are presented in Figure 7.

The traction system of high-speed trains will deteriorate under long-term operation, leading to various early failures. If these early failures are not successfully detected, they evolve into safety incidents. To detect early faults in the traction system, Chen et al. [73] introduced a method based on Kullback Leibler divergence and independent component analysis (ICA), and the experimental results showed that the method could diagnose three early faults in the train traction system with higher computational efficiency. To effectively diagnose early faults in train traction systems, Wang et al. [74] designed an improved relevant vector machine (RVM) approach based on a Bayesian framework and demonstrated the effectiveness of the method with practical cases. To improve the accuracy of fault diagnosis of train traction motors under external disturbances, Tian et al. [75] developed a method based on interference isolation with an unknown input observer. To identify early faults in the traction system of trains more accurately, Wu et al. [76] advanced a method based on improved total measurable fault information residual (ToMFIR) and validated the effectiveness of the proposed method by simulation models. Insulated-gate bipolar transistor (IGBT) is the main power supply component of traction systems in high-speed trains, and to improve the accuracy of fault diagnosis of IGBTs, Fei et al. [77]

presented a method based on wavelet transform and SVM. In order to diagnose the typical faults of traction systems effectively, both simulation-driven and data-driven methods are effective [78,79]. Zhang et al. [80] proposed a method based on statistical indicators and fuzzy clustering, which was verified by experimental data from the train traction control system. By constructing a nonlinear fault dynamics model for high-speed trains, Tao et al. [81] proposed a method for fault-tolerant control based on state observation.

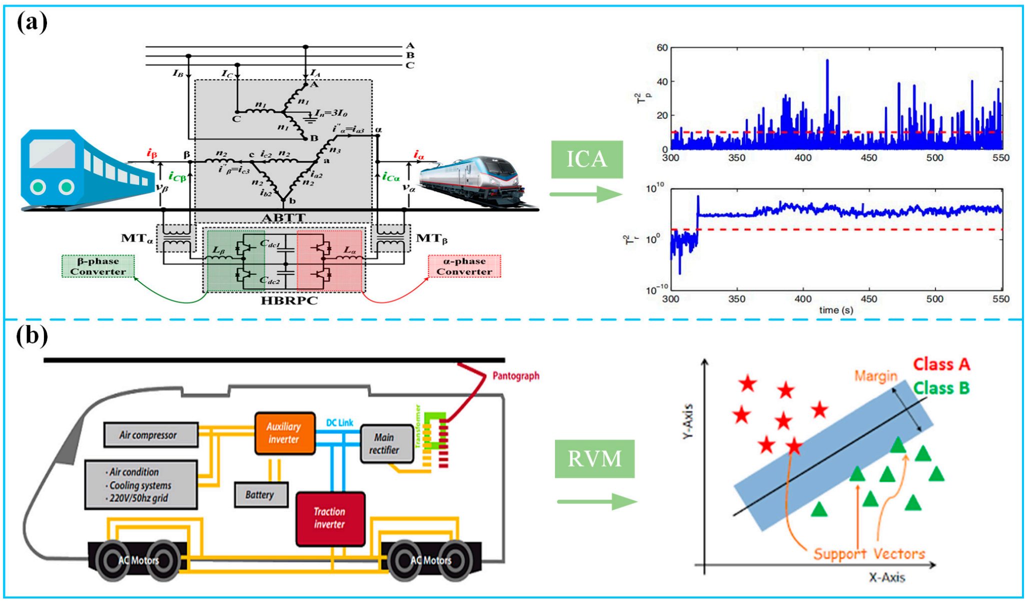

Figure 7. Fault diagnosis method of traction system: (**a**) independent component analysis (ICA) [73]; (**b**) relevant vector machine (RVM).

Therefore, the fault diagnosis of the train's traction system is mainly made by pattern recognition, and the main models used include ICA, relevant vector machine, ToMFIR, SVM, etc.

3.2. Fault Diagnosis of Train Braking System

The braking system of trains mainly consists of brake units, brake cylinders, and related brake components. The complex service environment of high-speed trains, coupled with long-distance driving, leads to various early failures that inevitably occur. If these early failures are not detected in time for maintenance, safety accidents may occur. Therefore, it is important to carry out fault diagnosis research on the train braking system, and its main fault diagnosis methods are shown in Figure 8.

Combining the concepts related to inter-variate variance (IVV) and the idea of four-stage division, Ji et al. [82] proposed a fault detection method based on refined IVV (R-IVV) and stage monitoring indicators, which can improve the accuracy of early fault diagnosis of the train's braking system. To address the problem of data imbalance in train brake system fault detection, Liu et al. [83] presented a diagnostic framework based on a support vector machine (SVM), which improved the computational efficiency from the aspects of feature brush selection, feature selection, and model construction, and verified that the method had better results through experiments. Sang et al. [84] advanced a method based on data domain description and a variable control limit, which can detect three kinds of early failures of high-speed train braking systems and effectively reduce the false alarm rate. Guo et al. [85] designed an improved convex packet vertex-based method to diagnose multiple faults in the train's braking system accurately.

Therefore, the fault diagnosis of train braking systems is mainly made by failure mode identification, and the main methods include IVV, feature selection, SVM, etc.

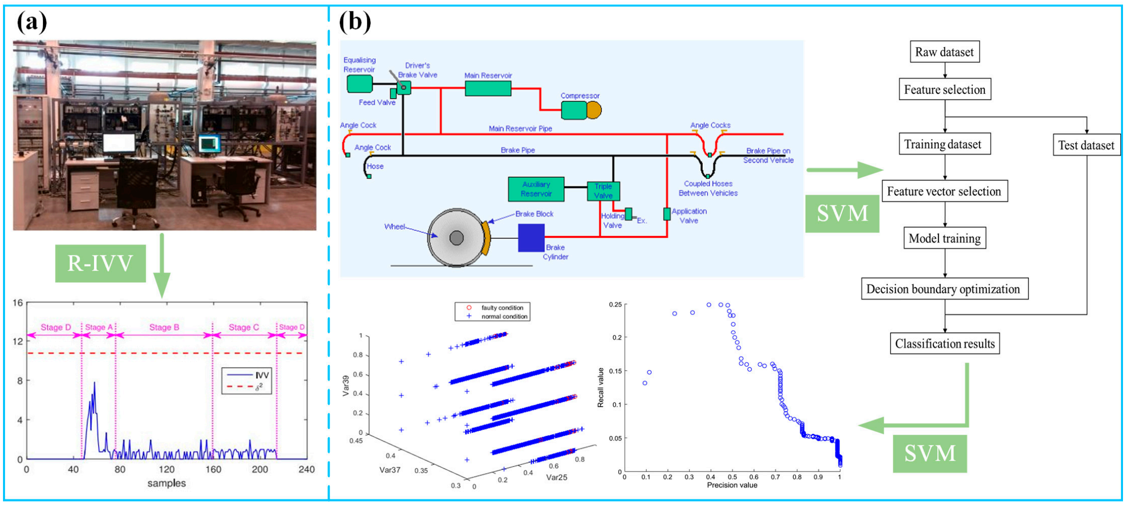

Figure 8. Fault diagnosis method of brake system: (**a**) refined inter-variate variance (R-IVV) [82]; (**b**) support vector machine (SVM) [83].

4. Fault Diagnosis of the High-Speed Train Electrical System and Information Control System

4.1. Fault Diagnosis of Train Electrical System

High-speed train electrical systems are extremely complex and prone to performance degradation and early failure of their internal components due to various uncertainties (overload, unexpected disturbances, and extreme environmental changes). If these early faults are not detected in time, it affects the safe operation of trains. Therefore, it is important to perform the diagnosis of early faults in the train electrical system, and the main diagnostic methods applied are presented in Figure 9.

The long-term operation of high-speed trains in various harsh environments makes it inevitable that the actuators and sensors in the electrical system will suffer performance degradation and even more serious failures. If not addressed in a timely manner, minor malfunctions can eventually turn into catastrophic consequences. To accurately diagnose early faults of asynchronous motors in high-speed trains, Wu et al. [86] constructed a kinetic model based on a squirrel-cage induction motor with a d-q coordinate system, which has high sensitivity and accuracy. To address the problem of serious difficulty in detecting compound faults in electrical systems under multi-source disturbances, Bai et al. [87] proposed a detection method that assigns different faults in coupled signals to separate subspaces, which can effectively improve diagnostic capability. To effectively detect early faults in the slanting support lines of the suspension chain network, Yang et al. [88] presented a deep learning detection method based on fast RCNN Resnet 101 and YOLO V2, which achieves the detection of faults and their localization with high accuracy and robustness. Yao et al. [89] proposed a deep learning foreign object detection method based on YOLO V3, which combines the advantages of migration learning and data augmentation and is not only easier to train but also improves the accuracy of foreign object detection in train electrical systems. To address the problems existing in the manual inspection of train electrical systems, Han et al. [90] advanced an automatic machine vision-based inspection method, which uses CNN to extract crack faults and then uses a fast algorithm to perform further identification of the region of interest. Combining the advantages of traditional hierarchical analysis, maximum absolute weighted residuals, and maximum entropy, Liu et al. [91] developed a comprehensive weighting algorithm (CWA), and the experiments proved that the proposed method has good practical application value. To detect early faults of capacitors in train electrical systems, Oukhellou et al. [92] designed a method based on Dempster–Shafer classification fusion, which improves the accuracy of fault detection. To increase the accuracy of diagnosing different fault states in train electrical systems, Liu et al. [93] proposed a discrete Hidden Markov method based on k-mean clustering, which uses Lloyd's algorithm to quantify the collected sample vector set and can effectively identify six different kinds of faults.

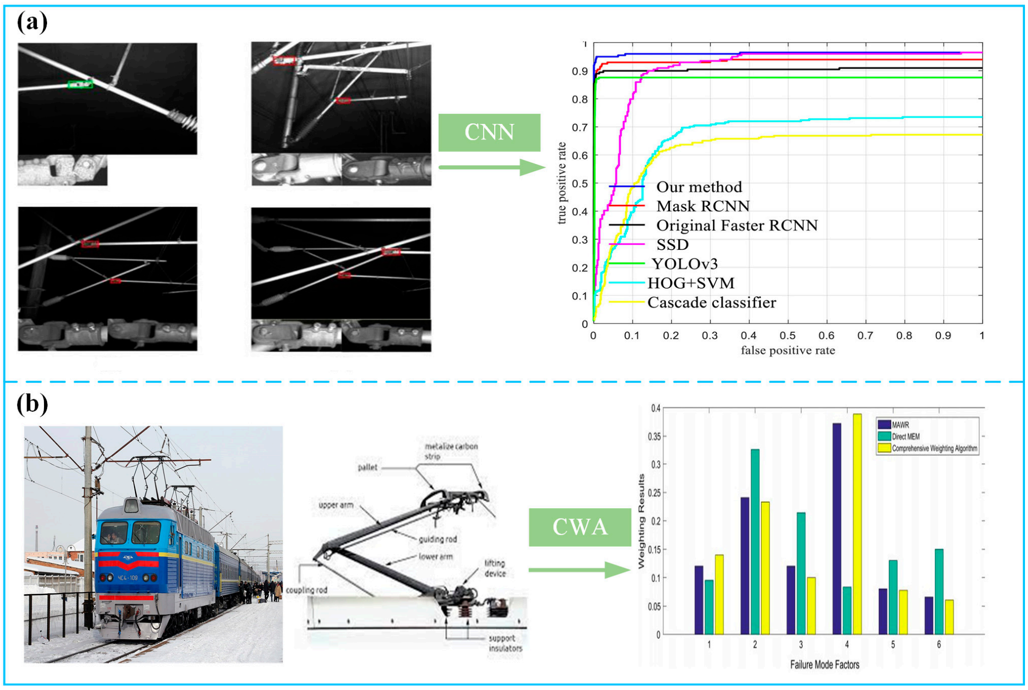

Figure 9. Fault diagnosis method of electrical system: (**a**) convolutional neural network (CNN) [90]; (**b**) comprehensive weighting algorithm (CWA) [91].

Therefore, the fault diagnosis of train electrical systems is mainly made by pattern recognition, mainly applying Resnet, CNN, CWA, YOLO, and discrete hidden Markov models.

4.2. Fault Diagnosis of the Train Information Control System

The information control system of high-speed trains mainly consists of a detection unit, a control unit, an input unit, an output unit, a communication unit, display equipment, and other auxiliary equipment. During the long service life of a train, the components of the information control system develop early failures, which affect the stability of the train. Therefore, it is important to carry out the fault diagnosis of the information control system of high-speed trains to ensure the safe operation of trains, and the main diagnostic methods applied are displayed in Figure 10.

To quickly detect faults in the information control system of trains, Xu et al. [94] introduced a big data-driven approach based on Hadoop, MySQL, and HDFS as the basic framework for realistic user-oriented fault diagnosis and fault prediction. To enable more accurate fault detection and isolation, Niu et al. [95] designed a method to improve the Petri net, which uses PCA to monitor the state of the vibration signal from the acquisition and can achieve the detection and isolation of information control system faults. To achieve a rapid diagnosis of early faults in information control systems, Cai et al. [96] developed an approach based on a train safety sensor network (TSSN), which is accomplished in concert with a multi-layer sensor, a train data center, and a ground data center. Huang et al. [97] advanced a method based on support vector regression (SVR) and Kalman filter (KF), which not only reduced the calculation time but also improved the accuracy of state prediction of the information control system. Aiming at the inaccuracy of fault diagnosis in the train information control system, Yin et al. [98] presented a method based on a vehicle-mounted deep belief network (DBN), which was verified by actual fault data of the Wuhan–Guangzhou high-speed railway and was better than the traditional method. In order to diagnose the faults of the information control system of high-speed trains more comprehensively, Liu et al. [99] proposed a method based on a deep fault tree and quantitative analysis, and the effectiveness of the proposed method was verified by experiments. Huang et al. [100] proposed a method based on fault trees and fuzzy D-S evidence inference, which was shown to be effective for fault prediction and diagnosis through experiments. To improve the accuracy of fault diagnosis in information control systems, Zhou et al. [101] designed a method based on a transferable belief model and multi-sensor data fusion, which was validated experimentally.

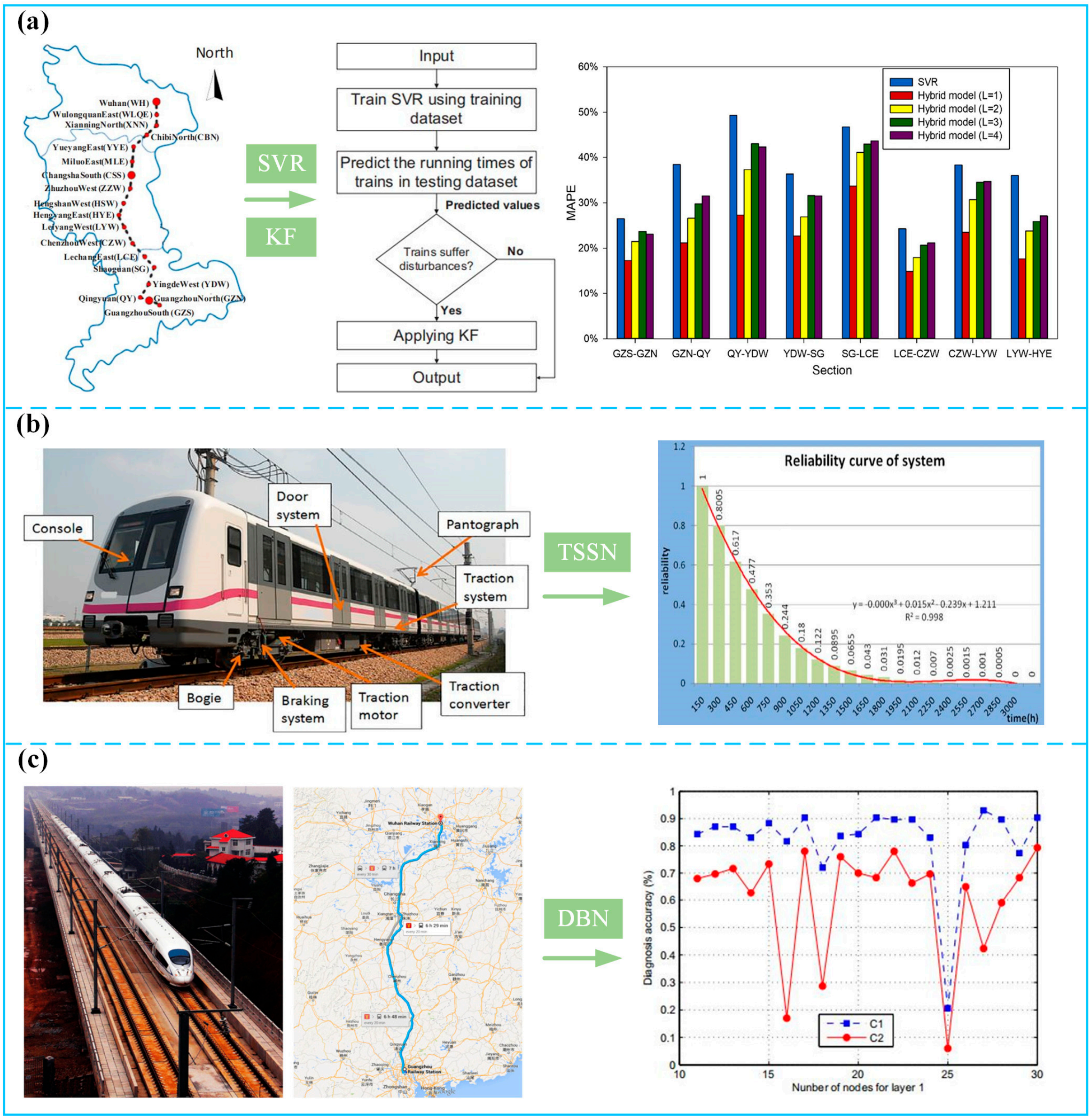

Figure 10. Fault diagnosis method of information control system: (**a**) support vector regression (SVR) and Kalman filter (KF) [97]; (**b**) train safety sensor network (TSSN) [96]; (**c**) deep belief network (DBN) [98].

Therefore, the fault diagnosis of an information control system is mainly made by pattern recognition, and the main methods used include PCA, the deep belief network, TSSN, the Kalman filter, the fault tree, D-S evidence, etc.

5. Applicability of Fault Diagnosis Methods for the High-Speed Train

In summary, the fault diagnosis of each key system of high-speed trains is mainly realized by fault feature extraction and fault pattern recognition, and the main methods used are shown in Figure 11. In addition, the applicability of the same method in different systems was categorized, as shown in Table 1. From Table 1, the Kalman filter can be applied to the fault diagnosis of the bogie system and the information control system at the same time. Secondly, support vector machines can be used not only in the bogie system (bearings, suspension system, and wheels) but also in the traction system and brake system fault diagnosis. Thirdly, the principal component analysis can enable not only the effective fault diagnosis of bogie systems (bearing and wheel) but also the fault diagnosis of information control systems. Additionally, morphological filters are mainly used in the fault diagnosis of bogie systems (bearing, cardan shaft, wheel) and information control systems. Furthermore, convolutional neural networks are mainly applied to the fault diagnosis of bogie systems and electrical systems. Therefore, the Kalman filter, support vector machine, principal component analysis, morphological filter, and convolutional neural network are widely used in train fault diagnosis and have good applicability and robustness in different systems. Moreover, the main methods used in the fault diagnosis of bogie systems are empirical modal decomposition, variational modal decomposition, wavelet transform, singular value decomposition, and support vector machines.

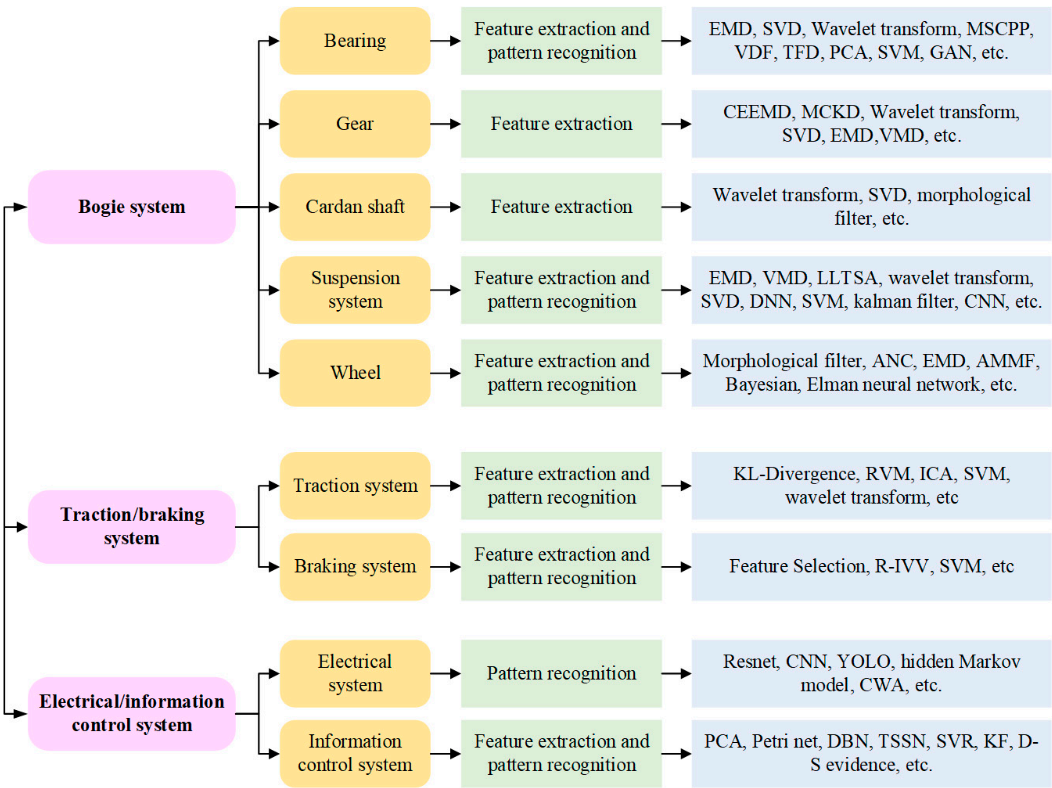

Figure 11. The main fault diagnosis methods used in the key systems of high-speed trains.

Table 1. Applicability of main fault diagnosis methods.

Methods	Key Systems
Empirical modal decomposition	Bogie system (bearing, gear, suspension system, wheel), etc.
Variational modal decomposition	Bogie system (bearing, gear, suspension system), etc.
Wavelet transform	Bogie system (bearing, gear, cardan shaft), traction system, etc.
Singular value decomposition	Bogie system (bearing, gear, cardan shaft, suspension system), etc.
Kalman filter	Bogie system (suspension system), information control system, etc.
Support vector machine	Bogie system (bearing, suspension system, wheel), traction system, braking system, etc.
Principal component analysis	Bogie system (bearing, wheel), information control system, etc.
Morphological filter	Bogie system (bearing, cardan shaft, wheel),
Convolutional neural network	information control system, etc.

6. Discussion and Conclusions

While enjoying the convenience and comfort of high-speed trains, increasing attention has been paid to their safety during service. In addition, as a piece of large and complex equipment, the performance degradation and early failure of various key systems inevitably occur during the service of high-speed trains, thus affecting the safe operation of trains. Therefore, condition monitoring and fault diagnosis of key train systems are of great value and are increasingly becoming a difficult challenge.

Through the previous review, it was known that the fault diagnosis of key systems of high-speed trains is realized by feature extraction and pattern recognition, but it is mainly carried out by the traditional manual inspection, test bench, and video monitoring, which still has many shortcomings. Firstly, existing fault diagnosis methods do not work online on a large scale. Secondly, the monitoring data collected is not comprehensive and objective enough, which restricts the in-depth research on the fault diagnosis of key train systems. Third, the practicality of the existing methods needs to be further improved to be applied to the fault diagnosis of high-speed trains. Therefore, this review has the following prospects:

(1) Developing online monitoring technology can ensure the reliability and safety of high-speed trains. This can not only quickly identify early failures of key systems but also predict performance degradation, thus establishing a long-term warning mechanism.
(2) By installing various sensors (voltage, current, vibration acceleration, displacement, and pressure) in the key system of the train, a large number of real train operation data and corresponding historical data can be obtained, which provides data support for train fault diagnosis based on the combination of big data and experience knowledge.
(3) With the advantages of machine learning and deep learning, a big data-driven condition monitoring and fault diagnosis platform for key systems of high-speed trains is being developed. This can shift from traditional planned repairs to condition repairs and forecast repairs, thereby reducing annual maintenance costs and preventing potential safety accidents.

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