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A review of the application of deep learning in intelligent fault diagnosis of rotating machinery

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ABSTRACT

With the rapid development of industry, fault diagnosis plays a more and more important role in maintaining the health of equipment and ensuring the safe operation of equipment. Due to large-size monitoring data of equipment conditions, deep learning (DL) has been widely used in the fault diagnosis of rotating machinery. In the past few years, a large number of related solutions have been proposed. Although many related survey papers have been published, they lack a generalization of the issues and methods raised in existing research and applications. Therefore, this paper reviews recent research on DL-based intelligent fault diagnosis for rotating machinery. Based on deep learning models, this paper divides existing research into five categories: deep belief networks (DBN), autoencoders (AE), convolutional neural networks (CNN), recurrent neural networks (RNN), and generative adversarial networks (GAN). This paper introduces the basic principles of these mainstream solutions, discusses related applications, and summarizes the application features of various solutions. The main problems of existing DL-based intelligent fault diagnosis (IFD) research are summarized as small-size sample imbalance and transfer fault diagnosis. The future research trends and hotspots are pointed out. It is expected that this survey paper can help readers understand the current problems and existing solutions in DL-based rotating machinery fault diagnosis, and effectively carry out related research.

1. Introduction

As a research hotspot in the field of prognosis and health management (PHM), intelligent fault diagnosis of rotating machinery (IFDRM) plays a significantly important role for rotating machinery systems in reducing both operation and maintenance costs and ensuring safe operations [1,2]. As a branch of IFD, machine learning (ML)-based fault diagnosis of rotating machinery generally has three diagnosis steps as follow. (1) Sensor data that can show the health status of equipment is collected. (2) The features are extracted from the collected data by various algorithms. (3) According to the extracted fault-sensitive features, various ML algorithms are used to identify and classify the faulty states of equipment. With the rapid development of DL, IFDRM is also developing rapidly. Compared with traditional shallow ML algorithms, DL algorithms have the following advantages in IFD [3,4].

1. Facing massive monitoring data of equipment working statuses in modern industry, it is impractical to completely or mainly rely on manual extraction of fault features. DL-based models have strong learning ability on big data and high generalization performance and can automatically extract fault features from sensor data without manual intervention. This significantly reduces the dependence on expert experiences and rich domain knowledge.
2. Shallow ML algorithms with a high-accuracy end-to-end diagnosis model between input data and faulty states are difficult to construct. DL algorithms can overcome the defects of shallow structure algorithms through multi-layer nonlinear transformation and can achieve high-precision fault diagnosis.

IFDRM covers rich research objects, including induction motors [5], helicopter gearboxes [6], wind turbines [7], and so on. According to existing related research, key components as the essential research objects usually include rotor systems, gearboxes, and bearings in rotating machinery. IFDRM mainly focuses on determining the health status of these key components. The related research and papers on DL-based IFDRM are continuously being published in recent years. Fig. 1 shows the search results of the Web of Science Core Collection database from 2017 to 2021, with the names of several major rotating machinery, fault diagnosis, and various DL algorithms as subject

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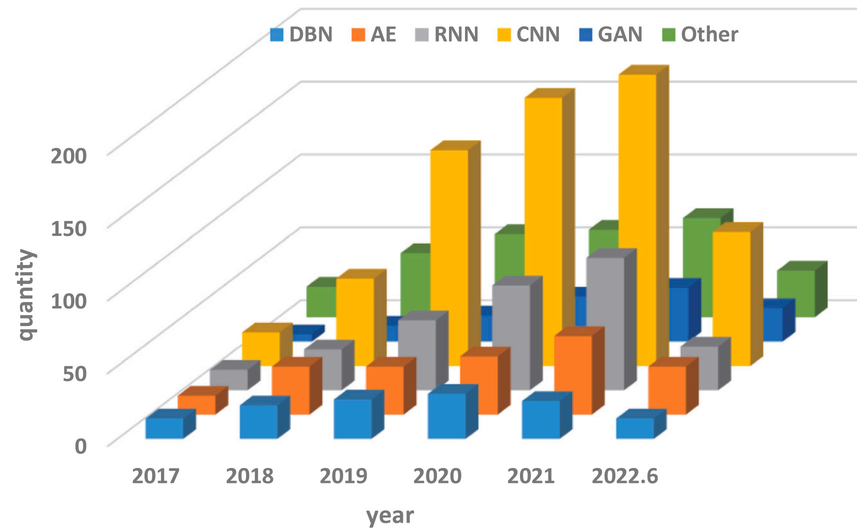


Fig. 1. The number of DL-based IFDRM literature published in recent years. Taking DBN as an example, the basic query = ((DBN OR deep belief network) AND (fault OR condition monitoring OR health management OR intelligent diagnosis)).

keywords. Other models mainly include multilayer perception (MLP), deep neural network (DNN), and self-organizing map (SOM), which are rarely used in recent years. Fig. 2 shows the approximate proportion of literature sources in the RMIFD field collected in this paper, all of which are included in the SCI core database. Most of them are indexed by Scopus and IEEE databases. The existing DL-based IFDRM literature is numerous but disorganized. There are three main reasons as follows.

1. There are many types of DL algorithms. IFD methods vary, which integrate one/multiple DL algorithms into traditional algorithms.
2. IFD methods usually include multiple stages such as data preprocessing, feature extraction, and feature classification. DL algorithms can be applied to one or multiple stages to process different tasks.
3. DL-based IFD applications have differences in fault diagnosis objects, data acquisition conditions, and equipment working environments.

Considering the above-mentioned reasons, it is necessary to summarize relevant studies in a timely manner. Reviewing the methods and results of the existing literature will help researchers to conduct richer research in the future. Some existing reviews summarize related research from different perspectives. According to existing reviews of AI-based mechanical fault diagnosis (FD), DL-based methods are playing an increasingly important role and are considered to have high development potential [3,5,8–11]. For IFDRM, Manikandan et al. [12], Duan et al. [13] and Saufi et al. [14] reviewed the principles and applications of ML algorithms and DL algorithms in mechanical IFD. A large number of studies have shown that the failures of key components such as bearings and gears account for a considerable proportion of rotating machinery failures. Neupane et al. [15], Zhang et al. [16], Tang et al. [17] and Singh et al. [18] summarized and discussed DL-based fault diagnosis methods for specific components of rotating machinery such as bearings, gears/gearboxes, and pumps. Yang et al. [19] reviewed the application and progress of autoencoders from the two aspects of optimization and combination, and pointed out the challenges and prospects of AE-based fault diagnosis research. As shown in Fig. 1, compared with other DL algorithms, most of the existing IFD applications are developed based on CNN. Tang et al. [20] discussed the basic structure and principles of CNN, and focused on analyzing and summarizing the applications of CNN-based fault diagnosis for rotating machinery. Data preprocessing is an important step in DL-based IFDRM methods. Tang et al. [21] and Soother et al. [22] provided an overview of data preprocessing methods and focused on analyzing existing data preprocessing methods used in DL-based IFD. The above-mentioned two papers are conducive to related research on data preprocessing methods in DL-based IFD methods. Zhang et al. [23] studied the progress of DL in PHM and concluded that the nature of fault detection, fault diagnosis and RUL prediction tasks include binary classification, multi-classification and continuous regression. Rezaeianjouybari et al. [24] provided a systematic review of PHM frameworks based on advanced DL algorithms, and discussed the limitations and challenges of existing technologies as well as future mainstream research directions. Zhang et al. [25] reviewed the research on intelligent fault diagnosis of machinery with imbalanced small-size data, and divided existing methods into data augmentation-based, feature extractor-based, and classifier-based designs.

In existing studies, DL-based diagnosis methods achieve excellent performance in common fault diagnosis of rotating machinery. However, most of existing methods need to assume both training and testing data have the same data distribution. In actual industrial scenarios, differences in data distribution are inevitable due to changes in various working conditions, natural wearing of equipment, and equipment itself [26]. The performance of most models degrades severely when any difference exists in data distribution between training and testing sets. Retraining a new model requires a large amount of labeled data. However, obtaining labeled samples in new scenarios is often difficult. Therefore, it is necessary to explore how to apply previously established models in related domains to new diagnosis scenarios. This type of fault diagnosis is called transfer fault diagnosis (TFD) [27]. From the perspective of domain adaptation (DA), TFD focuses on applying diagnosis models trained in source domain to target domain. In recent years, transfer learning (TL) and domain adaptation techniques have been introduced into IFDRM to accomplish this type of task. With the development of TFD, some existing reviews summarized the related research. Zheng et al. [28] first summarized state-of-the-art cross-domain fault diagnosis research. The review was conducted from three perspectives, research motivation, cross-domain strategies, and application objects. Jiao et al. [27] comprehensively summarized and discussed the applications of CNN-based mechanical FD from the perspectives of fault classification, life prediction, and TFD. Li et al. [29] introduced various deep transfer architectures and related theories, and further discussed the main achievements, challenges and future research directions of deep transfer learning in TFD. Yan et al. [30] summarized the applications of knowledge transfer in fault diagnosis of rotating machinery into four categories, transfer between multiple working conditions, transfer

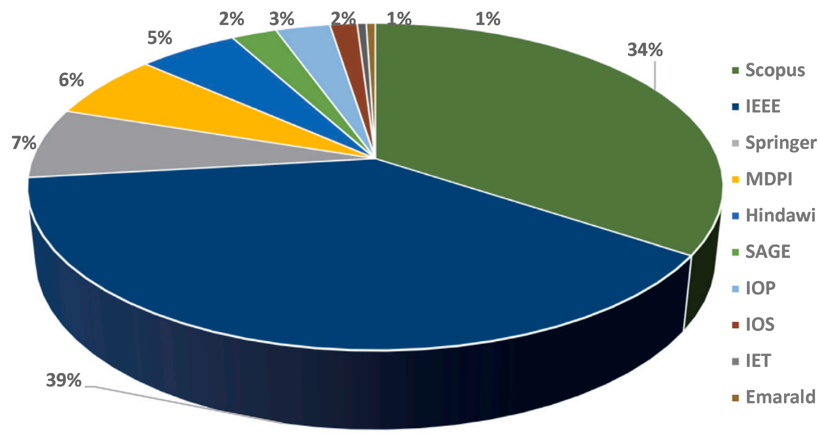


Fig. 2. The distribution of literature sources, including: Elsevier Scopus, IEEE/IET Electric Library, SpringerLink, MDPI Journal database, Hindawi Journal database, SAGE Journal database, IOP Science, IOS Press, IET (Institution of Engineering and Technology), Emerald Journal database.

between multiple locations, transfer between multiple machines, and transfer between multiple fault types.

With the widespread application of ML algorithms in IFD of machinery, Lei et al. [1] comprehensively summarized the development process of IFD, including expert systems, traditional machine learning, deep learning, and transfer learning, and summed up existing research of DLIFD. In addition, the application of TL in IFD of machinery was predicted and a comprehensive summary was made. This paper has an important guiding significance for understanding the development of IFD and conducting IFD-related research. Zhao et al. [31] summarized the implementation details of specific DL algorithms, including data processing methods, construction of diagnosis models, etc., and studied the performance of different methods on different public datasets. This review tried to establish a benchmark for fair comparisons in subsequent studies. It published some open-source codes. It focused on discussing state-of-the-art DL algorithms for the fault diagnosis of rolling bearings. This review is greatly conducive for researchers to understand and learn existing IFD methods. Existing reviews have comprehensively summarized a large number of IFD studies from various perspectives.

However, as more and more new studies are published, the latest research directions and basic methods of IFD have changed. Some published reviews only provide an incomplete summary of DL in IFDRM. To address the issue, this survey paper reviews state-of-the-art research on DL-based IFDRM. The reasons for this review and the contributions of this review can be summarized as follows.

- As shown in Fig. 1, DL-based IFDRM research has developed rapidly in recent years. These newly published methods are likely to reflect new research directions and trends. The applications of GAN and GRU (Gated Recurrent Unit) have gradually increased in the past three years. The number of published CNN-based methods is increasing dramatically. The research related to TFD has gradually emerged in recent years. However, the above-mentioned methods still lack sufficient summary and generalization. Therefore, a timely review of the latest research is necessary.
- Existing literature focuses on model improvement, with an increasing focus on the learning and representation process of fault information used in DL models. Numerous studies on corresponding improvements have been published in these areas. Existing literature lacks a summary of where and why DL-based methods are improved (the unique problems with DLIFD). This survey paper attempts to summarize and discuss the relevant contents.

Table 1
Commonly used open-source rotating machinery datasets.

Dataset	CWRU	IMS	PU	PHM2009	SEU	MFPT	XJTU-SY
Frequency	85	14	12	7	7	6	4

- Many methods are strongly correlated. By analyzing the different improvement points of these similar studies, the current research directions are summarized and future research trends are predicted. This survey paper can help readers clearly understand the application conditions, advantages and disadvantages of various DL algorithms in IFD, and guide readers to recognize the challenging issues in DL-based IFD-related research.

The rest of this paper is structured as follows. Section 2 introduces several public datasets commonly used in related research of IFDRM; Section 3 elaborates popular DL algorithms and the corresponding applications in IFDRM; Section 4 discusses existing research from the perspectives of both problem and method; and Section 5 concludes this paper.

2. Commonly used public datasets in IFDRM

DL-based IFD is realized based on a large amount of high-quality data. If this premise cannot be met, the diagnosis performance of DL-based models is difficult to meet expectations. Data collection can be achieved by various types of sensors. Vibration signals are the most popular and commonly used data. However, it is difficult to obtain enough high-quality data in actual industrial scenarios. There are some problems in data collection, such as sparse fault data, long acquisition time, and high cost. Fortunately, many well-known institutions have published various datasets for public research and related applications. This section briefly introduces some commonly used and recognized datasets. Existing studies typically combine public datasets and self-collected data to verify the proposed method. Table 1 shows the public datasets of rotating machinery commonly used in 159 instances in the literature discussed in this paper.

2.1. CWRU bearing dataset

The dataset of bearing vibration signals [32] provided by Case Western Reserve University (CWRU) is one of the most popular open-source rotating machinery datasets and is often used as a benchmark dataset in various published studies to verify the effectiveness of the corresponding methods. The CWRU bearing dataset is rich in variety and can be used for various comparative experiments. It contains four load conditions: 0, 1, 2, and 3Hp; two sensor positions: fan end and drive end; four fault levels: 0, 0.007, 0.014, and 0.021 inches; four fault types: rolling element, inner ring, outer ring, and healthy status. Bearing faults were obtained by electrical discharge machining (EDM). The main data was collected at the sampling frequency of 12 kHz or 48 kHz, and the sampling time was 10 s. The overlapping method was often used to increase the number of samples. This dataset is often used in the research of TFD between different loading conditions and different locations and is also suitable for the research of different failure degrees. The CWRU bearing dataset can be downloaded from https://engineering.case.edu/bearingdatacenter.

2.2. IMS bearing dataset

The dataset of bearing vibration signals [33] provided by NSF I/UCR Center for intelligent maintenance systems (IMS) was collected from three test-to-failure experiments, including four types of faults: rolling element, inner ring, outer ring, and healthy status. All bearing failures occurred beyond service life. The sampling frequency was 20 kHz. The duration of each sampling was 1s, including 984 to 4,448 sample files. Since the faults were generated in the working process, this dataset is often used in the research of real-world and early-stage fault detection. The IMS bearing dataset can be downloaded from https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/.

2.3. PU bearing dataset

The bearing dataset [34] provided by the Bearing Data Center of Paderborn University (PU) contains 32 sets of current signals and vibration signals. This dataset contains four working conditions; three kinds of bearings: no fault, artificial fault, and real fault caused by accelerated life experiment; five fault types: healthy status, artificial inner ring, artificial outer ring, real inner ring, and real outer ring. This dataset is suitable for comparative experiments and information fusion research of different types of sensor signals. It is also suitable for comparative experiments between real-world faults and artificial faults. The PU bearing dataset can be downloaded from https://mb.uni-paderborn.de/kat/forschung/datacenter/bearing-datacenter/.

2.4. PHM2009 gearbox dataset

The vibration signal dataset of industrial gearboxes provided by PHM IEEE 2009 Data Challenge [35] contains five kinds of rotational speed; two kinds of loading conditions; three kinds of faulty components: bearing, gear, and shaft. Each component has different fault types. Sensors were installed at two positions. The sampling frequency was 66.67 kHz. Compared with other datasets, this dataset contains multiple hybrid faults of gears and bearings and has more advantages in the study of composite gearbox failures. The PHM2009 gearbox dataset can be downloaded from https://phmsociety.org/public-data-sets/.

2.5. SEU gearbox dataset

The dataset of gearbox vibration signals [36] provided by Southeast University (SEU) consists of a bearing dataset and a gear dataset. It contains two kinds of speed and loading conditions: 20 Hz–0 V and 30 Hz–2 V. Gears have five fault types including healthy status, chipped tooth, missing tooth, root fault, and surface fault; Bearings have five fault types including: healthy status, inner ring, outer ring, inner+outer ring, and rolling element. It can be used in the research of both TFD of working conditions and fault diagnosis of different components. The SEU gearbox dataset can be downloaded from https://github.com/cathysiyu/Mechanical-datasets.

2.6. MFPT bearing dataset

The bearing dataset of mechanical failure prevention technology (MFPT) [37] contains three fault types, including healthy status, inner ring, and outer ring. Both inner ring and outer ring contain seven working conditions: 0 lbs (inner ring)/25 lbs (outer ring), 50 lbs, 100 lbs, 150 lbs, 200 lbs, 250 lbs, and 300 lbs. Researchers often regard similar faults under different working conditions as different kinds of failures. This dataset is suitable for studying the mutual transfer between various working conditions. The MFPT bearing dataset can be downloaded from https://www.mfpt.org/fault-data-sets/.

2.7. XJTU-SY bearing dataset

The bearing dataset provided by the Institute of Design Science and Basic Component at Xi'an Jiaotong University and the Changxing Sumyoung Technology Company [37] was collected from three accelerated degradation experiments. The sampling frequency was 2.56 kHz, and the sampling time was 1 min. This dataset contains three speed-loading conditions: 35 Hz–12 kN, 37.5 Hz–11 kN and 40 Hz–10 kN. Run-to-failure data includes four fault types: inner race wear, cage fracture, outer race wear, and outer race fracture. This dataset can be used in the research of TFD and early-stage fault diagnosis. The XJTU-SY bearing dataset can be downloaded from https://biaowang.tech/xjtu-sy-bearing-datasets/.

2.8. Summary

The above-mentioned contents do not contain all the datasets of rotating machinery vibration signals. This paper only lists and briefly introduces several commonly used datasets. The CWRU dataset is highly recognized in the field of IFDRM. Fig. 3 visually demonstrates a section of vibration signals with the same length from the CWRU dataset under various conditions. According to the comparison of these waveforms, the fault type, fault degree, working condition, and measurement location have different degrees of influence on the measurement results, and changes in these conditions affect the performance of the fault diagnosis model to varying degrees. Besides the CWRU dataset, other datasets have similar characteristics. It is expected that the introduction to these datasets can help researchers select appropriate datasets according to their research goals.

3. Applications of DL algorithms in IFDRM

Several reviews published in recent years have summarized the DL algorithms commonly used in IFD, including DBN, AE, and CNN. According to the differences, LSTM [31], Resnet [1], or GAN [22] is categorized into a single class, respectively. LSTM as a variant of RNN is widely used in IFD. Resnet is a special structure of CNN. In addition, the applications of GAN in IFDRM are growing. Therefore, this paper summarizes the main DL-based IFD methods into the following categories: DBN, AE, CNN, RNN, and GAN.

This section introduces the applications of several popular DL algorithms in IFDRM. In order to sort out the existing literature, the current research is mainly introduced from the perspective of the main problems and improvement methods focused on by the literature.

3.1. DBN

DBN was proposed by Hinton et al. [38] in 2006. The commonly used DBN network is shown in Fig. 4. A BP network is usually added to the last network layer and used as a classifier [9]. The hidden layer state of the previous restricted boltzmann machine (RBM) is used as the visual layer input for the next RBM.

DBN as one of the most classic DL models was applied to IFDRM early. The number of DBN-based methods is growing slowly, but DBN is still one of the mainstream DL algorithms in IFDRM.

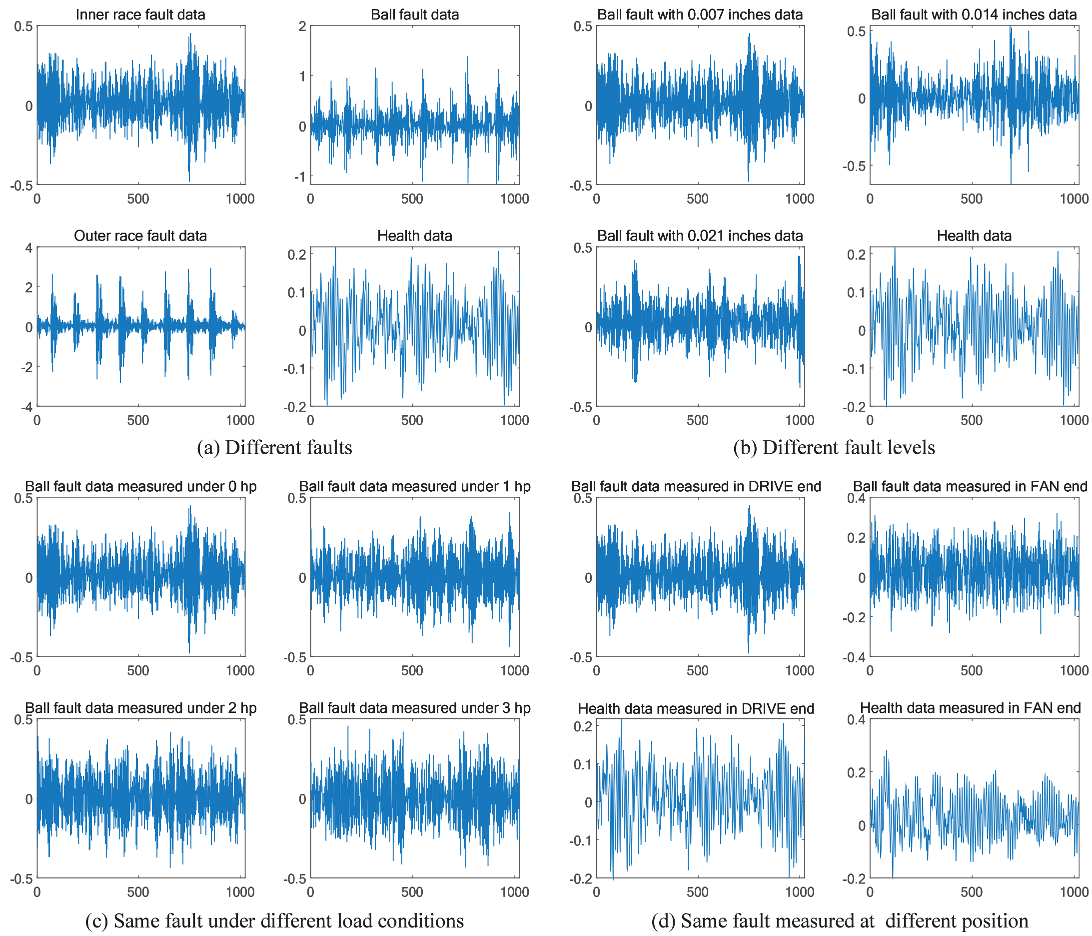


Fig. 3. The waveforms of vibration signals from the CWRU dataset. (a) Different faults (b) Different fault levels (c) Same fault under different loading conditions (d) Same fault measured at different positions.

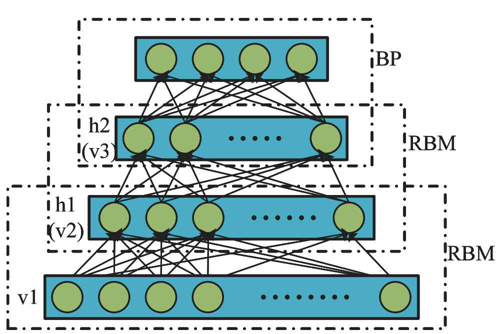


Fig. 4. General structure of DBN.

3.1.1. Applications of DBN in IFDRM

DBN can extract effective fault features from feature sets constructed according to specific tasks. Tamilselvan et al. [39] extracted time-domain and frequency-domain features from the collected multivariate time series and applied these features to DBN training to achieve the classification of aircraft engine failures. Chen et al. [40] constructed a low-dimensional feature set as the input of DBN according to intrinsic mode functions (IMFs) obtained by the vibration signals processing through the integrated empirical mode decomposition (EEMD). In order to make full use of the data from sensors installed at different positions to improve the reliability of diagnosis results, Chen et al. [41] proposed a sparse autoencoder-deep belief network (SAE-DBN) model. This method uses SAE to fuse the time-domain and frequency-domain features of each sensor signal, and then applies the fused feature vectors to DBN training to achieve the classification of rotating machinery faults. Lv et al. [42] proposed a semi-supervised fault diagnosis method for aero-engine based on denoising autoencoder (DAE) and deep belief network (DBN). Apply DAE to unsupervised learning of faulty samples to achieve denoising and dimensionality reduction features. Put the extracted features and sample labels into DBN for supervised learning.

Various signal processing techniques are used to preprocess signals so that DBN can learn high-quality fault features [43]. Shao et al. [44] applied double tree complex wavelet package transform (DTCWPT) to preprocess vibration signals to refine fault information, and constructed DBN to extract fault-sensitive features from the feature set of each frequency band, thereby improving the diagnosis accuracy of both rolling bearing compound faults and corresponding fault severity. Wang et al. [45] used the optimized Morlet wavelet to process vibration signals. The time-domain and frequency-domain features were extracted from vibration signals and pulse signals, respectively. DBN was trained to realize the fault diagnosis of planetary gearboxes. Guan et al. [46] applied empirical mode decomposition (EMD) to decompose the diagnosis signals into IMFs with different signal-to-noise ratios (SNR), and reconstructed signals through the sample entropy of the IMFs to train DBN. The results confirmed that this method was superior to the mechanical structure fault diagnosis. Pan et al. [47] applied discrete wavelet packet transform to process vibration signals, calculated the energy characteristics of each frequency band, and sent them to DBN for diagnosis, which proved that the energy index has strong sensitivity to bearing faults. Guo et al. [48] innovatively used the double sparse dictionary method to preprocess the original signals and tried to overcome the problem that the time–frequency domain features sometimes cannot express faults well. The obtained sparse feature coefficients as the input of DBN were applied to achieve higher and more stable diagnosis accuracy of bearing faults. Han et al. [49] calculated the wavelet packet energy entropy (WPEE) and multi-scale permutation entropy (MPE) of vibration data. A feature matrix was formed, and the improved DBN was applied to extract deep fault features from the formed feature matrix. Liu et al. [50] used threshold-based amplitude-aware permutation entropy (AAPE) to first determine the existence of any fault, and then applied a feature extraction method integrating both DTCWPT and generalized composite multi-scale amplitude-aware permutation entropy (GCMAAPE) to fully extract fault features and send them to DBN for fault classification. Lu et al. [7] used random Bernoulli matrix and compressed sensing (CS) to process the original vibration signals. Therefore, the data dimension decreased to reduce the amount of calculation and eliminate noise interference. Subsequently, the DBN optimized by chaos quantum particle swarm optimization (CQPSO) was used to extract fault features from the compressed samples. Finally, least-squares SVM (LSSVM) was applied to fault classification. As a variant of hierarchical DBN, hierarchical diagnosis network (HDN) was proposed by Gan et al. [51], which achieved two-stage diagnosis of both fault types and fault severity based on wavelet packet energy features. Jin et al. [52] proposed a bearing weak fault diagnosis method based on VMD and improved DBN. The signals are processed and features extracted using VMD, and the "hyperparameters" of the DBN are optimized using the Grey Wolf optimization algorithm (GWO).

In addition to signal preprocessing, some methods also optimize the construction and training process of different diagnosis models, thereby improving diagnosis accuracy. Xie et al. [53] introduced Nesterov momentum (NM) into the training process of DBN, and applied the individual adaptive learning rate algorithm to optimize the parameter update process, which improved the diagnosis accuracy. Tang et al. [54] and Shen et al. [55] took the frequency-domain signals of vibration signals as the input and adopted NM to accelerate the training process and improve training accuracy, thereby improving fault diagnosis accuracy of bearings. Yan et al. [56] constructed multi-scale cascading DBN (MCDBN) to extract important information from multi-scale vibration signals. This method used an improved multi-scale coarse-grained vibration signal processing. The spectra of vibration signals were calculated and sent to MCDBN. The related fault features were extracted in parallel. Shi et al. [57] applied the loss function of DBN to construct the convergence function of particle swarm optimization (PSO) to optimize DBN. This method used the feature matrix obtained by wavelet packet energy entropy (WPEE) as the input of DBN, and adjusted the learning rate according to the gradient value of the backpropagation process, thereby improving the diagnosis accuracy of rotating machinery under variable working conditions. Tang et al. [58] proposed a bearing fault diagnosis method called Bidirectional Deep Belief Network (Bi-DBN). A Quantum genetic algorithm (QGA) is applied to optimize the key parameters of Bi-DBN to improve the feature learning efficiency.

Some studies avoid artificial selection of features and learn fault features directly from raw signals. He et al. [59] used the unique training process of DBN to extract stable fault features through unsupervised greedy learning of RBM one by one, and applied GA algorithms to optimize network parameters. Compared with back-propagation neural network (BPNN) and support vector machine (SVM), this method achieved better performance. Jiang [60] adopted local preserve projection (LPP) to achieve deep feature fusion, which improved the quality of features extracted from raw vibration signals. Li et al. [61] used stacked sparse autoencoders to compress the original data and reduce its dimension, and then applied multiple Gauss-binary RBMs (GBRBMs) to diagnose gear pitting faults. Shao et al. [62] developed a novel convolutional DBN (CDBN) model and used AE to compress vibration signals, which tried to overcome the limitations of a single type of DL algorithm. In bearing fault diagnosis of electric locomotives, this method obtained better results than single DL models.

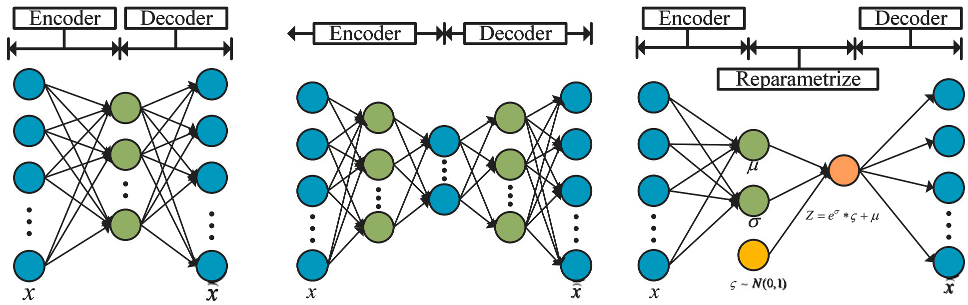
Some studies make full use of a large amount of unlabeled data to carry out research on unsupervised fault diagnosis of rotating machinery. Zhao et al. [63] used the unsupervised feature extraction layer of DBN and the improved adaptive non-parametric weighted-feature Gath-Geva (ANWGG) fuzzy clustering algorithm to construct an unsupervised diagnosis model termed deep fuzzy clustering neural networks (DFCNN). Li et al. [64] proposed an unsupervised diagnosis model based on SAE-DBN and binary processors. This method utilized SAE and binary processors to preprocess the original data and reduce its dimensionality. Binary codes were obtained, and the supervised fine-tuning process was abandoned during DBN training. Yan et al. [65] used the multi-source heterogeneous information composed of the shaft orbit plot generated from both vibration signals and original displacement signals as the input of DBN, which effectively determined the fault diagnosis of the motor rotor imbalance.

The related research of DBN-based TFD mainly focuses on the transfer fault diagnosis of load and speed change scenarios. Changes in load conditions lead to large differences in the data distribution of vibration signals of rolling bearings. Kang et al. [66] proposed a fault diagnosis model for variable load conditions based on mean maximum discrepancy (MMD) and CDBN. This method used CDBN to extract the features of the labeled data in the source domain and the unlabeled data in the target domain, and applied the MMD of the weighted mixed kernels to reduce the difference in feature distribution. The k-nearest neighbor algorithm was finally used to achieve feature classification. In addition to changes in load conditions, changes in rotation speed also cause differences in data distribution, which bring great difficulties to the generalization of fault diagnosis models. Che et al. [67] proposed domain adaptive-DBN (DA-DBN). The multi-kernel maximum mean difference (MK-MMD) was used as a regular term to reduce the distribution difference between source-domain and target-domain data. The original data and its time-domain and frequency-domain features were used as input to train DBN. Facing the problem of data distribution shift caused by changes in rotation speed and load conditions, Xing et al. [68] proposed a distribution-invariant DBN (DIDBN), which directly learned distribution-invariant features from vibration signals and then performed fault classification. This model consists of local connected RBM (LCRBM), fully connected RBM (FCRBM), and mean discrepancy maximum RBM (MDM-RBM), where MDM-RBM is used to reduce feature distribution differences. Zhao et al. [69] proposed a transfer fault diagnosis method based on JDA and Deep Belief Network (DBN), using the maximum mean difference as a metric to reduce the joint distribution difference between samples in the two domains.

3.1.2. Summary of DBN-based applications

According to the above-mentioned literature, the main steps of DBN-based IFDRM can be summarized as: (1) data preprocessing, (2) DBN construction, (3) DBN training.

Manual feature extraction is common in data preprocessing. Unlike traditional shallow machine learning algorithms, DBN can learn high-level feature representations from large amounts of data. End-to-end intelligent diagnostic models can be built by directly using the original signals or spectra, thereby reducing the reliance on expert experience and knowledge. However, due to the fully connected structure of the RBM, directly using the original signals with a higher sampling frequency as the input does not only considerably increase the amount of computation, but may also cause difficulty in model convergence. According to the existing literature, manually designing feature sets with the help of various signal analysis methods is still an important step for many existing DBN-based IFD methods. As the advantage of manually designing and extracting features, data dimensionality is reduced while fault information is preserved. Similarly, many existing methods use data compression and stacked autoencoders to reduce data dimensionality, and many experimental results confirm that these methods are effective.



(a) Auto-encoder (b) Stacked Auto-encoder (c) Varitional Auto-encoder

Fig. 5. General structure of AE and its variants (a) AE (b) Stacked AE (c) VAE.

In building DBN, existing literature uses various traditional optimization algorithms to determine key hyperparameters, such as the number of RBMs and the number of neurons in hidden layers. To improve the diagnosis performance, different strategies such as feature fusion and multi-scale feature extraction are employed to improve the structure of the DBN. In order to reduce the difference of feature distribution and realize cross-working-condition diagnosis, different domain-adaptive strategies such as MMD and MDM are embedded in DBN. Nesterov momentum and adaptive learning rate are the main improvements during DBN training. In addition, some methods utilize the greedy training process of DBN to extract features and use them in conjunction with other classification algorithms, thereby achieving unsupervised fault diagnosis. Most of the improvements in DBN-based IFD methods focus on data preprocessing. These methods try to design a feature set that can effectively preserve fault information and reduce the DBN computation.

3.2. AE

Auto-encoder (AE) was proposed by Hinton et al. [70] in 1986. It is an unsupervised algorithm consisting of an encoder and a decoder, as shown in Fig. 5(a). The encoder is used to map input signals to the hidden layer expression, extract high-dimensional data features, and realize dimensionality reduction. The decoder is used to restore the original input data in the hidden layer to complete data reconstruction. The update of AE parameter optimization is realized by establishing a loss function in the reconstruction process.

In IFDRM, the variants of AE are more widely used than ordinary AE. The commonly used variants of AE include stacked AE shown in Fig. 5(b), sparse AE (SAE), denoising AE [71] (DAE), convolutional AE [72] (CAE) and variational AE [73] (VAE) shown in Fig. 5(c).

As a classic algorithm for data dimensionality reduction and data feature extraction, AE-based methods still occupy a large proportion in the applications of IFDRM.

3.2.1. Applications of AE in IFDRM

Vibration signals from rotating mechanical components such as gears and bearings often contain noise, so it is difficult to extract effective high-quality features from these signals. As a variant of AE, DAE is often used to solve noise interference. Guo et al. [74] proposed a denoising and feature extraction method based on stacked denoising AE (SDAE), which does not require extensive professional denoising knowledge. This method directly extracts features from vibration signals and achieves better results than DBN. A DAE-based multi-level denoising (MLD) scheme designed by Jiang et al. [75] simultaneously learns general and detailed fault features from the complex spectrum of vibration data at different scales, thereby improving diagnosis accuracy. Yan et al. [76] constructed multi-domain metrics to train DAE by using signals from different domains, and simultaneously determined the model parameters of the stacked denoising autoencoders (SDAE) using a novel nature-inspired algorithm named grasshopper optimization algorithm. Xu et al. [77] used SDAE to extract preliminary features and applied cluster by fast search (CFS) to automatically find the available cluster centers based on the distance and local density between the features of each sample and its cluster centers, thereby implementing fault classification. Zhang et al. [78] proposed an ensemble deep autoencoder (EDAE), which was constructed by integrating sparse deep AE, denoising deep AE, and contractive deep AE (CDAE). Multiple types of AEs enable the ensemble model to efficiently handle redundant information, noise corruption, and signal perturbations.

In addition to noise, the complex operating conditions of rotating machinery make vibration signals non-stationary and nonlinear, which increases the difficulty of feature extraction. Shao et al. [79] adopted maximum correlation entropy to design a new deep autoencoder loss function, thereby enhancing the feature learning ability of vibration signals. This method also applies artificial fish swarm algorithm to optimize the key parameters of deep AE and obtains better results than BPNN and SVM. Wang et al. [80] proposed an enhanced depth feature extraction method based on Gaussian radial basis kernel function and auto-encoder (AE) called kernel AE (KAE), which tried to overcome the issues caused by the nonlinearity of vibration signals. Features are extracted from vibration signals layer by layer using KAE and multiple AEs. Tong et al. [81] used multi-scale analysis to extract multi-scale features from vibration signals as the input of AE, and applied the cuckoo search algorithm to automatically obtain the optimal hyperparameters, which improved the diagnosis performance of AE in complex working conditions. Li et al. [82] formulated two cost functions to preserve the local and global geometry of input samples respectively, resulting in good fault classification performance and short training and testing time. In order to determine the parameters of AE such as the number of layers and the dimension of the hidden layer, Zhang et al. [83] constructed a manifold sparse auto-encoder (MSAE) based on the eigenvalues of the manifold map. The dimension of each hidden layer is determined by the eigenvalues of the manifold map of hidden neurons, while the number of layers in a deep learning architecture is determined by the clustering distribution of features. Li et al. [84] proposed a local discriminant preserving extreme learning machine autoencoder (LDELM-AE) based on extreme learning machines with fast training speed and strong generalization ability, which used local geometry and local discriminants in vibration signals to learn data representations. Shao et al. [85] proposed an improved stacked autoencoder (MSAE) using adaptive Morlet wavelets to diagnose various fault types and severities of rotating machinery automatically. A Drosophila optimization algorithm is used to determine the tunable parameters of the Morlet wavelet to flexibly match the analyzed data's characteristics. Zeng et al. [86] proposed a Hierarchical Sparse Discriminant Autoencoder (HSDAE) method for fault diagnosis of rotating mechanical, using class aggregation and class separability strategies to constitute additional losses to enhance the feature extraction capability of the network.

It is difficult to collect fault data in actual industrial scenarios. The collected datasets are always unbalanced, which causes difficulties in achieving high-accuracy fault diagnosis. Therefore, some data augmentation methods were proposed by exploiting the reconstruction ability of AE. Dixit et al. [87] proposed an improved conditional variational autoencoder (CVAE) to generate high-similarity synthetic samples to solve the problem of insufficient training samples. Han et al. [88] proposed a fault diagnosis model data enhanced SAE (DE-SAE), and visualized the features learned by each layer of DESAE. Zhao et al. [89] first developed a novel imbalanced fault diagnosis method for rotating machinery based on deep Laplacian AE. The generalization performance of this fault diagnosis framework is improved, making it suitable for feature learning and classification of imbalanced data. Yang et al. [90] applied the bagging strategy to integrate the AE consisting of both the improved sparse autoencoder and the DAE into an AE-based fault diagnosis model. Saufi et al. [91] designed a DL model based on stacked sparse autoencoder (SSAE), and applied the PSO algorithm to optimize the key hyperparameters of SAE, so the fault diagnosis of gearboxes was achieved in the case of limited samples. Liu et al. [92] improved the quality of the generated data through embedding AE in GAN to learn deep features of real-world data.

Since existing methods such as DBN always highly depend on expertise such as signal processing and failure pattern recognition, it is better to directly utilize raw signals in fault diagnosis. Huang et al. [93] proposed a RNN-based VAE model suitable for the dimensionality reduction of time series, and then used principal component analysis (PCA) and linear discriminant analysis (LDA) to reduce the dimensionality of the compressed sequences again, thereby realizing the identification of failure modes. Li et al. [61] utilized stacked AE to compress raw vibration data to enhance model's diagnosis capability. Chen et al. [94] optimized the proposed convolutional autoencoder neural network (CANN) by minimizing the difference between input signals and reconstructed signals, thereby realizing unsupervised fault diagnosis.

In order to solve the lack of labeled samples in practical industrial scenarios, many AE-based methods have been proposed to realize transfer fault diagnosis. He et al. [95] designed a novel multi-wavelet AE to achieve fault diagnosis of gearboxes at different speeds. According to the spectral similarity coefficient, high-quality samples in the source domain were selected to train AE, and then a small number of samples in the target domain were used for fine-tuning. Zhiyi et al. [96] modified the loss function with non-negative constraints to improve the reconstruction effect and fine-tuned the model with limited labeled target-domain samples to achieve fault diagnosis model transfer between different bearings. Dong et al. [97] used sparse denoising AE to extract deep features from frequency-domain signals, and then introduced joint geometry and statistics to align and process sample features, reducing the statistical and geometric domain differences of samples under different working conditions. Liu et al. [98] proposed a new deep domain-adaptive model based on optimal transport (OT), which used AE to extract discriminative features of different fault types. An OT plan with a predefined cost function was searched between source and target domains. Domain-invariant representation features were trained by minimizing the difference in the joint distribution of OT-based features and label space. In response to the occurrence of new fault types in the target domain, Li et al. [99] proposed a two-stage transfer adversarial network (TSTAN) based on an adversarial learning strategy, which used an unsupervised CAE sub-network to automatically identify the number of unlabeled new fault types. For the IFDRM across noise domains, Xiao et al. [100] proposed noisy domain-adaptive marginal stacked denoising autoencoder (NDAmSDA), which transferred the constructed classifier from one noise domain to another noise domain and tested on the acoustic emission signal dataset of gearboxes. Lv et al. [101] proposed a diagnosis method based on conditional adversarial denoising autoencoder (CADAE). Transfer fault diagnosis can be completed, when the target domain has fault categories not included in the source domain. Zero-shot classification can be achieved for unknown fault types.

3.2.2. Application summary of AE

Similar to DBN, AE-based IFD methods can still be divided into three steps: (1) data preprocessing, (2) AE construction, and (3) AE training.

In the AE-based IFDRM methods, the input data of AE can be raw vibration signals, Fourier spectra, Hilbert envelope spectra, and time domain, frequency domain, and time–frequency domain statistical feature sets, etc. Due to the poor generalization performance and feature extraction ability of a single AE, these methods often use variants of AE such as DAE, SAE, VAE, and CAE and stacked models of these units. In addition, hybrid models such as CANN that integrate AE and CNN, and ELM-AE that integrates AE and ELM are also proposed. Various optimization algorithms such as PSO are applied to determine the optimal hyperparameters to improve diagnosis performance.

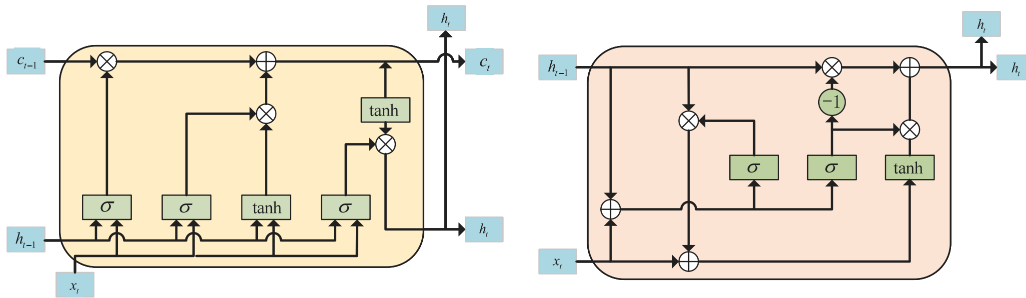
In the AE-based IFDRM methods, AE mainly has two functions (1) data enhancement, such as data expansion and data noise reduction; (2) feature extraction. These methods mainly use the encoder part to obtain low-dimensional high-level feature representation, which is convenient for the classifier to perform fault classification. A large number of existing studies have shown that the features extracted by AE still have strong data distribution characteristics, and are often used to extract fault features in transfer fault diagnosis.

3.3. RNN

As a special feature of RNN, the previous information can be used to reflect into the current state and a predicted value is output [102], which gives RNN unique advantages in processing time-series data. Most of the current IFD research focuses on the time series of vibration signals, so the applications of RNN-based IFDRM have grown rapidly. Most RNN-based methods are mainly composed of various improved variants of applied RNNs: LSTM [103] as shown in Fig. 6(a) and GRU [104] as shown in Fig. 6(b).

3.3.1. Application of RNN in IFDRM

Zhao et al. [105] proposed a local feature-based gated recurrent unit (LFGRU) network to learn deep feature representations from hand-designed features. Liao et al. [106] proposed a one-dimensional CNN-GRU composite model to learn the vibration signals reconstructed by data segmentation, which tried to overcome the important information loss of vibration signals caused by manual feature extraction and then determined fault types. Tao et al. [107] proposed a multi-layer gated recurrent unit (MGRU) method for gear fault diagnosis. As the number of MGRU layers increased, the features of different fault types can be more accurately identified. Yu et al. [108] proposed a hierarchical fault diagnosis model based on stacked LSTM to learn fault feature representations directly from vibration signals, which achieved better results than shallow machine learning algorithms. Durbhaka et al. [109] used LSTM to achieve fault classification of gearboxes based on vibration signals and adopted multiple swarm intelligence models to optimize the LSTM model. CarNet proposed by Zhang et al. [110] allows the diagnosis model to be fully trained on a limited dataset. This method proposes an equitable sliding stride segmentation (ESSS) data augmentation method to expand the data scale and enhance the spatiotemporal correlation of the related data. It uses CNN and bidirectional GRU to extract shallow spatial features and deep temporal information respectively, and achieves high diagnosis accuracy. Cao et al. [111] input the real rotor speed to the transmission system testing bench of wind turbines to simulate the actual time-varying non-stationary operating conditions, which used LSTM to learn the fault feature representation from time-domain features, thereby improving the diagnosis capability of the fault diagnosis model under changing operating conditions. Aljemely et al. [112] designed a method combining long short-term memory and large margin nearest neighbors, LSTM-LMNN, which uses the orthogonal weight initialization technique to memorize the key information of faults during the parameter update process.



(a) Structure of LSTM Unit (b) Structure of GRU Unit

Fig. 6. General structure of LSTM and GRU (a) LSTM (b) GRU.

In order to make the fault diagnosis model take advantage of multiple DL models, some existing methods proposed different DL-based methods integrated with LSTM or GRU. Chen et al. [113] used CNN to initially extract features from vibration signals, and then used LSTM to further downsample and identify fault types, which considerably reduced the number of model parameters. Liu et al. [114] used the reconstruction error between the predicted data and the actual data output by GRU-based nonlinear predictive denoising autoencoders (GRU-NP-DAEs) to detect abnormal conditions and perform fault classification, which can effectively overcome the negative impact of noise. Considering that a single CNN method ignores the temporal relationship of time series, Zhang et al. [115] applied GRU units to network construction to learn feature representations from two-dimensional images stacked in time series, and then used MLP to classify the features. Ning et al. [116] proposed an improved ShufflenetV2-LSTM intelligent fault diagnosis system. It retains the ability of the ShufflenetV2 network to extract features, and also inherits the advantages of LSTM to enhance the ability of data sequence, thus improving the accuracy of fault diagnosis. Li et al. [117] proposed a method based on Wasserstein Generative Adversarial Network (WGAN) and Long Short-Term Memory Fully Convolutional Network (LSTM-FCN) to extract more robust and representative fault features through parallel feature extraction and fusion techniques.

Fault detection at an early stage is significantly important for the operation and maintenance of rotating machinery. Some existing studies have been carried out in order to achieve effective diagnosis of early-stage faults. Shi et al. [118] proposed a fault diagnosis method integrated with LSTM and SDAE. SDAE is used to denoise vibration signals. LSTM predicts the vibration signals of the next cycle according to the output of SDAE and uses the reconstruction error between the actual signals and the predicted signals in the next cycle to detect abnormal states. Abdul et al. [119] extracted easily computable hybrid feature sets from vibration signals and utilized LSTM for the diagnosis of early-stage faults. Kong et al. [120] proposed a new attention recurrent AE hybrid model, which enabled the network to extract the most valuable features in the input signals by adjusting the weight ratios of two loss functions and simultaneously optimizing the multi-branch network. The hybrid model can effectively extract the time-dependent data features by introducing a long short-term memory network to AE.

In order to solve TFD problems such as working condition changes in practical application scenarios, many studies have proposed various methods based on RNN variants. Zheng et al. [121] proposed an intelligent fault diagnosis method called normalized recurrent dynamic adaptation network (NRDAN) based on the LSTM network integrated with layer normalization (LN). It not only adapts the marginal and conditional distributions of both domains simultaneously, but also dynamically and quantitatively estimates the relative importance of the two distributions to enable transfer fault diagnosis across devices. Tang et al. [122] proposed a fault diagnosis method of rotating machinery diagnosis integrated with entropy gain ratio and semi-supervised transferable LSTM network (EGR-STLSTM) for different working conditions. This method fine-tunes the STLSTM model obtained by training the source-domain feature set with a small amount of labeled target-domain data. Similarly, Song et al. [123] proposed a fault diagnosis method under variable loading conditions based on an improved elastic network and an LSTM network. It used a small amount of target-domain data to fine-tune the model and applied transfer learning of an improved elastic network to suppress overfitting, which improved the efficiency of model training. Zhu et al. [124] also adopted the method of fine-tuning target-domain samples and introduced L1 regularization to the training of LSTM network, which improved the diagnosis accuracy and generalization ability of the model. Zhao et al. [125] proposed a transfer fault diagnosis method based on a small amount of labeled target-domain data. A bidirectional GRU is used to generate auxiliary samples in source domain, and then the manifold embedded distribution alignment (MEDA) is used to align the data distribution of auxiliary samples in the source domain and unlabeled samples in the target domain. Zhuang et al. [126] proposed a fault diagnosis method based on stacked residual dilated convolutional neural network (SRD-CNN). It removed partial noise with the help of the unique input gate structure of LSTM, thereby improving the adaptability of the model to loading conditions. Jang et al. [127] introduced a new inter-domain latent spatial transformation method. It applied spatial attention to learn the latent feature space, and used a one-dimensional CNN-LSTM model to maximize the inter-class distance within the domain, thereby effectively improving the generalization performance of the model. Miao et al. [128] proposed a fault diagnosis model based on the transfer hidden layer, which used LSTM to extract features and fine-tuned model parameters with a small number of target-domain samples. Additionally, dropout was introduced to further reduce the demand for training data. Zhu et al. [129] proposed a framework for running state calibration based on deep learning and fuzzy synthesis. After that, three feature-based transfer learning methods are employed to narrow the difference between WTG data distributions to achieve migration fault diagnosis.

3.3.2. Application summary of RNN

Similar to the IFD methods based on DBN and AE, the fault diagnosis process of the IFD methods based on RNN and its variants can still be divided into three stages: data preprocessing, model construction, and model training. Hand-designed feature sets and vibration signals are still the main data types of model input. The dimension of the input data is usually limited by the size of the model and the amount of computation. Reducing or overcoming reliance on expert experience and domain knowledge is a common problem.

The applications of RNN variants in IFD are mainly developed based on LSTM and GRU, especially the multi-layer and bidirectional structure models. Due to the unique advantages of RNN in processing time series, many existing solutions use RNN variants or combine RNN variants with other classification algorithms, trying to preserve the temporal correlation of vibration signals during feature extraction to improve diagnosis performance. Few existing solutions propose methods for the selection of RNN model hyperparameters. In the training

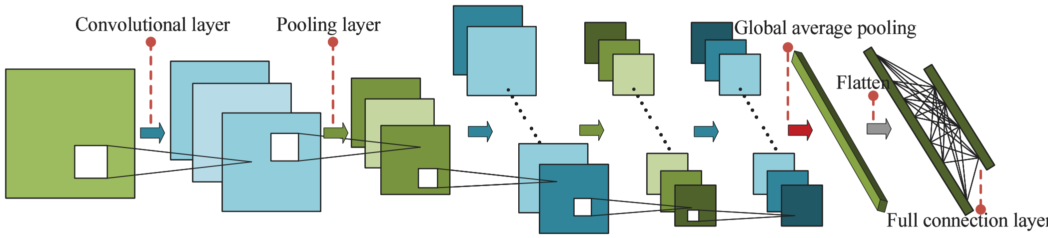


Fig. 7. The general structure of CNN.

Table 2
CNN-based IFDRM literature. 1-D and 2-D refer to the dimensions of the input data.

Problem	Input data type	Literature
Relying on domain knowledge and expert experience	1-D	[106], [134], [135], [136], [137], [138], [139], [140], [141]
	2-D	[142], [143], [144], [145], [146], [147], [148], [149]
Particular flaws in the features extracted by CNN	1-D	[137], [138], [139], [140], [150], [151], [152], [153], [154], [155], [156], [157], [158], [159], [159], [160], [161], [162], [163]
	2-D	[164], [165], [166], [167], [168], [169], [170], [171] [172]
Transfer fault diagnosis (TFD) issues	1-D	[137], [138], [139], [140], [173], [174], [175], [176], [177], [178], [179], [180],
	2-D	[181], [182], [183], [184]
Others	–	[185], [186], [187], [188], [189], [190], [191]

process of RNN-based IFD models, the features of the output data of LSTM or GRU with the same dimension are used as input data, so the reconstruction error between the predicted data and the actual data can be constructed to guide the model training.

In conclusion, RNN has the recognized ability to maintain the temporal correlation of features, and is often used to achieve feature extraction in IFD methods, which is mainly used as a feature extractor in hybrid models.

3.4. CNN

Convolutional neural network (CNN), inspired by the perception mechanism of biological visual cortex, first appeared in the LeNet network model proposed by LeCun [130] in 1989. Due to its powerful image processing capability, a large number of CNN-based models have been proposed, such as VGGNet [131], GoogleNet [132], and Resnet [133]. The structure of a common two-dimensional CNN shown in Fig. 7 mainly includes a convolutional layer, a pooling layer, and a fully connected layer.

CNN is a feedforward neural network with three most salient features: (1) local receptive field, (2) parameter sharing, and (3) pooling. The local receptive field and weight sharing strategy enable CNN to process large-scale data with fewer parameters, which is conducive to processing high-frequency vibration signals. Among the current mainstream DL models in the IFDRM field, IFD methods based on CNN and its variants are developing rapidly, which are the most mainstream DL-based IFDRM methods now. Due to the large number of CNN literature, it is not convenient to enumerate in large numbers. Table 2 summarizes CNN-based IFDRM. Among them, 1-D and 2-D represent the dimension of the input data of the CNN model. Some of them are specified in the following sections.

3.4.1. Application of CNN in IFDRM

Ince et al. [134] adopted 1-D CNN to quickly and accurately realize early-stage fault detection of motor bearings directly based on vibration signals, overcoming the dependence of traditional methods on expert experiences and domain knowledge. Wen et al. [142] utilized the advantages of CNN in processing images in the field of computer vision (CV) and stacked vibration signals into two-dimensional images. Compared with SVM, DBN and Sparse Filter, higher diagnosis accuracy is achieved by using the LeNet-5-based CNN model. Besides vibration signals, the fault information contained in the acoustic emission signals [143] can also be effectively utilized by CNN. The complex working environment and complex rotating mechanical structure lead to complex vibration signal components. In order to solve the difficulties caused by these external and internal factors, many methods have been proposed to enhance the features extracted by CNN in various ways. Since there is no general consensus on which frequency band contains the most intrinsic information about the health status of planetary gearboxes, Zhao et al. [164] developed a variant of Resnet based on dynamic frequency band weights to improve the feature extraction ability of CNN. Since there is no general consensus on which wavelet basis functions can be used for diagnosis, Zhao et al. [165] developed a fusion method based on wavelet coefficients, which tried to obtain a more complete time–frequency representation of vibration signals and used the fusion results to train a CNN-based diagnosis model. Zhao et al. [150] uniquely designed an adaptive rectified linear unit (APReLU) from the activation function inside CNN to improve the feature learning ability of CNN. A multi-scale CNN (MSCNN) proposed by Jiang et al. [151] simultaneously extracts multi-scale features through a multi-branch structure to obtain complementary and rich diagnosis information, thereby extracting “multi-scale features” contained in vibration signals. Peng et al. [152] proposed a multi-branch architecture with denoising branches to extract complementary fault information. Similarly, based on the idea of fusing complementary information, Wang et al. [153] trained a CNN by stacking the vibration signals of multiple sensors into a 2D image, so that the CNN can extract richer features. Zhang et al. [144] proposed a method called convolution neural network with training interference (TICNN), which used wide convolution kernels in the first layer of CNN to suppress high-frequency noise and introduced noise during training to enhance the noise immunity of the model and improve the diagnosis performance of the model in noisy environments. An enhanced CNN (ECNN) proposed by Han et al. [166] uses dilated convolution to enlarge the receptive field, which comprehensively obtains short-range and long-range fault information and captures long-range dependencies between vibration signals.

When traditional CNN extracts features, continuous downsampling operations may cause the loss of some important information. Some studies have proposed corresponding solutions to this problem. Li et al. [154] proposed a DL model called CNNEPDNN that integrated CNN with deep neural network (DNN), which achieved higher diagnosis accuracy than BPNN, ordinary CNN, and DNN. Wang et al. [145] constructed a cascade-structured CNN (C-CNN) to solve information loss.

Some existing methods try to process more types of input data, assisting CNN to extract more effective fault information from them. Jia et al. [146] first introduced the popular image feature extraction method to the fault diagnosis of rotating machinery based on infrared thermography (IRT), which used CNN to extract features from IRT. Qiu et al. [155] used feature extraction methods such as time-domain analysis, frequency-domain analysis, and wavelet analysis to construct a feature space containing 52 features for deep CNN (DCNN) training.

Some unique CNN models have been proposed for imbalanced data in healthy and faulty states. Jia et al. [185] proposed a framework called deep normalized convolutional neural network (DNCNN) and developed a neuron activation maximization (NAM) algorithm to implement the diagnosis of imbalanced data. Li et al. [173] proposed a transfer fault diagnosis model based on conditional alignment and adversarial domain adaptation, which used a conditional alignment layer to solve the problem of imbalanced label spaces in training and testing sets.

In solving TFD tasks, most of existing work focuses on developing cross-domain diagnosis models that can reduce the difference in data distribution. Training and testing sets are usually set as source-domain data and target-domain data, respectively. Li et al. [176] designed a cross-sensor transfer fault diagnosis model, which used domain-adversarial training to achieve the fusion of source- and target-data edge domains. Therefore, sensor data from different locations is complementary in use. Jin et al. [178] proposed a cross-loading fault diagnosis method called multilayer adaptive convolutional neural network (MACN). Adaptive batch normalization and MK-MMD were integrated, which reduced feature distribution difference in the shallow and deep layers of the proposed model respectively. Cao et al. [171] studied the case of speed variation and load variation, and developed a cross-domain fault diagnosis model called Y-Net, which used soft joint maximum mean difference (SJMMD) to reduce the marginal and conditional distribution differences of features. Zhu et al. [184] proposed a cross-device fault diagnosis method based on multi-adversarial training, which can make full use of existing data from multiple source domains.

3.4.2. Application summary of CNN

The general steps of CNN-based IFDRM methods can still be summarized as: (1) data preprocessing, (2) model construction, (3) model training. Unlike DBN, AE and RNN, CNN is more capable of handling two-dimensional data due to its unique shared weights and local receptive field strategy, which can be clearly observed in the research literature. Among the CNN-based IFDRM methods, a majority of the methods convert the vibration signals into a two-dimensional image as the input of the CNN. Similar methods are rarely used in other DL-based models. The processing steps for vibration signals are usually simple. Most approaches attempt to build end-to-end fault diagnosis models, rather than using hand-designed features or employing complex signal processing methods to process raw data.

To overcome the negative impacts of nonlinearity of vibration signals and noise interference, many improvements have been made in the structure of CNN and its variants, including multi-branch structure, cascade structure, attention module, dynamic coefficient module, etc. These improvements enhance the feature extraction ability of CNN to a certain extent. In the model training stage, adversarial training is increasingly employed to reduce the differences in data distribution across domains, enabling transfer fault diagnosis. The optimization of training strategies such as adaptive learning rate and batch normalization has not been described as the focus of most literature.

Many CNN-based IFD methods focus on the research of cross-domain fault diagnosis, which benefits from the flexible structure of CNN and its powerful feature extraction ability. CNN can cope with rich one-dimensional or two-dimensional input data, and can also easily process the results of signal transformations such as wavelet time–frequency maps, IRTs, and recursive matrices.

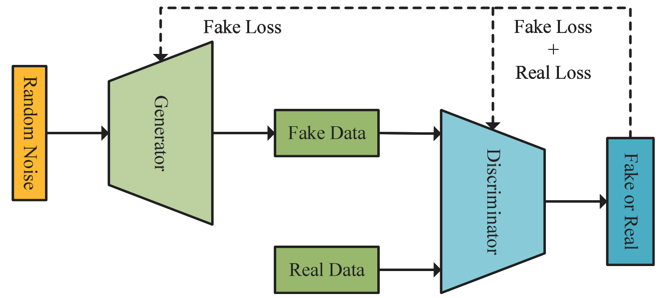


Fig. 8. General structure of GAN.

3.5. GAN

GAN was first proposed by Goodfellow et al. [192] in 2014. GAN is an unsupervised learning algorithm that makes two independent neural networks play against each other to achieve learning. As shown in Fig. 8, the general structure of GAN usually includes a generative model G and a discriminative model D, in which the generative model G is used to capture the input data distribution and G is trained to maximize the probability of making mistakes in D. The discriminative model D is used to estimate the probability that the sample comes from the training data instead of G. D is trained to identify whether the sample comes from G. GAN provides an excellent generative model. This model does not rely on any prior knowledge and does not need to assume that the data obeys a certain distribution. This model uses maximum likelihood to estimate data distribution. In practical applications, GAN has many variants, such as deep convolutional GAN (DCGAN), conditional GAN (CGAN) and auxiliary classifier GAN (ACGAN) [193].

Compared with other DL algorithms, GAN is more recent and has fewer applications of IFDRM. However, adversarial training endows GAN with powerful learning and generative capabilities, which makes GAN and its variants popular among researchers.

3.5.1. Application of GAN in IFDRM

Generally, the data often shows a long-tailed distribution. The proportion of healthy data is significantly larger than that of fault data. So, data imbalance adversely affects the fault diagnosis ability of the model. Therefore, GAN with good generative ability is increasingly applied to solve this problem [194]. Zareapoor et al. [195] proposed a DL model based on auxiliary classifier GAN (ACGAN), which is named as minority oversampling GAN (MoGAN). Using a generator, the model can generate samples of the minority class(es) to balance the dataset. With the improved discriminator, the model can simultaneously detect and classify faults. Li at al. [196] combined the advantages of ACGAN and Wasserstein generative adversarial network (WGAN), introduced a gradient penalty mechanism, and proposed the ACWGAN-GP model for the expansion of imbalanced datasets. According to the experimental results, this model is able to generate data that is highly similar to real-world samples. Wang et al. [197] proposed a fault diagnosis method for imbalanced data based on conditional variational autoencoder generative adversarial network (CVAE-GAN), which used the generative model of VAE as the generator and also used the adversarial training method of GAN to optimize model parameters. Liu et al. [198] proposed a diagnosis method that integrated multi-sensor data fusion techniques and data generation techniques. Data generated by GAN was used for data compensation and time series of multiple sensor data were concatenated to form fused data. Xie et al. [199] applied DCGAN to generate data to solve the data imbalance problem, which took a two-dimensional matrix of stacked spectrums of vibration signals as the network input. Liang et al. [170] used GAN to augment the wavelet time–frequency image dataset well. Guo et al. [200] used ACGAN to generate fault data, and then applied the generated data and real data to train a fault classifier, which effectively improved the fault diagnosis accuracy of bearings. A multi-GAN-based fault diagnosis method developed by Ding et al. [201] uses an ensemble strategy that controls each GAN to learn the relevant data distribution and achieves higher diagnosis accuracy than a single GAN in few-shot learning tasks. Wang et al. [202] proposed a novel fault diagnosis method integrating SDAE and GAN, which used SDAE as the discriminator. This model achieved good anti-noise performance. Cao [203] trained a GAN using two-dimensional images stacked by vibration signals and applied its discriminator to achieve fault classification in the same way as ACGAN. Verstraete et al. [204] proposed a novel DL-based generative adversarial fault diagnosis method. DCGAN and information maximizing GAN (InfoGAN) were used to synthesize image samples of unknown categories and known categories, respectively. PCA and K-means algorithm were applied to cluster the feature vectors output by the discriminator, and then fault types were determined.

In order to ensure the diversity and accuracy of the generated samples, some studies are devoted to improving the quality of the generated samples. Luo et al. [205] integrated the advantages of CGAN and DCGAN and proposed a fault diagnosis method of unbalanced data based on the C-DCGAN-based generative model. Zhao et al. [206] designed an online sample filter and an AE-based sample similarity estimation method to improve the quality of the generated samples. Comparative experimental results demonstrated the advantages of this method in fault diagnosis of unbalanced data. Zhou et al. [207] proposed a GAN model with SAE as the generator. SAE was used to generate fault features instead of inputting samples to avoid problems such as gradient disappearance. Additionally, another DNN was used as a fault classifier. Zhang et al. [208] proposed a multi-module generative adversarial network with an enhanced adaptive decoupling strategy. Adjusting each intermediate output of the generator with class labels prevents the effect of conditional control from diminishing as the transmission path extends. Wang et al. [209] proposed a Dual Attention Generative Adversarial Network (DAGAN). Enhance feature extraction with an attention model and improve feature representation. Extract features and generates fault samples using DAGAN.

It is not a common practice to directly use GAN to complete TFD, but domain-adversarial neural network (DANN) constructed based on the idea of GAN adversarial learning plays an important role in transfer fault diagnosis. The corresponding applications have been introduced in the application section of other DL algorithms. The principles of DAN will be introduced in the discussion section. Guo et al. [210] proposed a domain-adaptive method called generative transfer learning (GTL) to achieve cross-workload diagnosis, which consisted of a feature extractor, a classifier, and a domain discriminator. The proposed GTL takes short time furious transform (STFT) time–frequency map as input and can improve the classification rate under various workloads. The experimental results confirm that this method not only has higher accuracy but also converges faster than other domain-adaptive methods. Xiang et al. [211] proposed a domain separation reconstruction adversarial network (DSRAN) for transfer fault diagnosis between machines. The idea of GAN was applied to facilitate the network to learn domain-invariant features. Peng et al. [212] used GAN to supplement the labeled source-domain samples and integrated the parameter transfer learning method to achieve transfer fault diagnosis under the condition of small samples.

3.5.2. Application summary of GAN

GAN-based IFD methods can still be divided into the following steps: (1) data preprocessing, (2) model construction, (3) model training. Data preprocessing methods used in GAN-based methods usually transform the original signals into one-dimensional or two-dimensional signals. Due to the structure of GAN, the input of GAN is usually time-domain signals, frequency-domain signals or time–frequency domain signals. The generation ability of GAN plays an important data compensation role in fault diagnosis in the face of small sample size and data imbalance. Methods such as online filters and DAE integrated with GAN improve the quality of synthetic data. The ACGAN with the added fault classifier can directly complete the fault classification. The application of GAN in IFDRM mainly focuses on data generation. Adversarial training methods have also been confirmed to be beneficial for improving diagnosis accuracy.

4. Discussion

According to many studies, the general workflow of DL-based IFDRM methods can be summarized as shown in Fig. 9. In most of methods, the processed data or raw data is sent to the feature extractor for feature extraction, and then the classifier is used to classify features. DL models often integrate the feature extractor and the classifier. Finally, the predicted values and labels output by the classifier are used to construct the loss, and the parameters of the DL model are updated through backpropagation. The state-of-the-art studies have figured out existing problems in each stage of DL-based IFDRM methods, and have also studied these problems and proposed the corresponding solutions.

This section summarizes the problems and methods raised by various studies, then analyzes the advantages and disadvantages of various types of DL algorithms applied to IFDRM, and finally gives an outlook on future research trends.

4.1. Main problems faced by DL-based IFDRM

Compared with the traditional signal analysis methods and the IFD methods based on the shallow ML algorithm, the DL-based DRMRM methods have lower requirements for signal preprocessing and use a more complex and variable deep neural network to extract features without extensive experiences and knowledge guides, so the corresponding results are easier to understand. The DL-based IFD methods have great advantages in realizing end-to-end fault diagnosis models, but the special diagnosis process and model structure introduce some serious problems to DLIFD methods. A portion of the literature discussed in the previous section has explored these potential problems and proposed the corresponding solutions. The current problems mainly include fault diagnosis of imbalanced small-size samples and transfer fault diagnosis among other problems.

4.1.1. Fault diagnosis with small and imbalanced data

Deep-structured DL models usually have many parameters. These parameters rely on a large amount of labeled data, and good diagnosis results can be achieved through supervised learning. Sufficient high-quality labeled data is a prerequisite for the application of DL-based IFDRM methods [213]. However, insufficient data is common in engineering application scenarios. This differs from the data acquisition process in the laboratory. In practical applications, it is not practical for the equipment to run for a long time in a fault state, which causes serious harm to the normal operation of the entire mechanical system. Therefore, the data collected in actual scenarios presents a long-tailed distribution, which contains far more health data than fault data. The lack of high-quality fault samples leads to the fault diagnosis on imbalanced small-size data [25], which brings challenges to the training of deeply structured DL models. Serious data imbalance may exist between health data and fault data as well as between data of different failure types. Fig. 10(a) shows the fault diagnosis under the

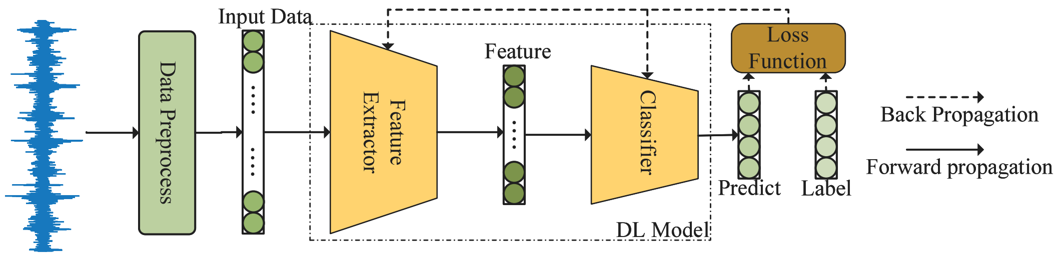


Fig. 9. Diagnosis workflow of DL-based IFDRM methods.

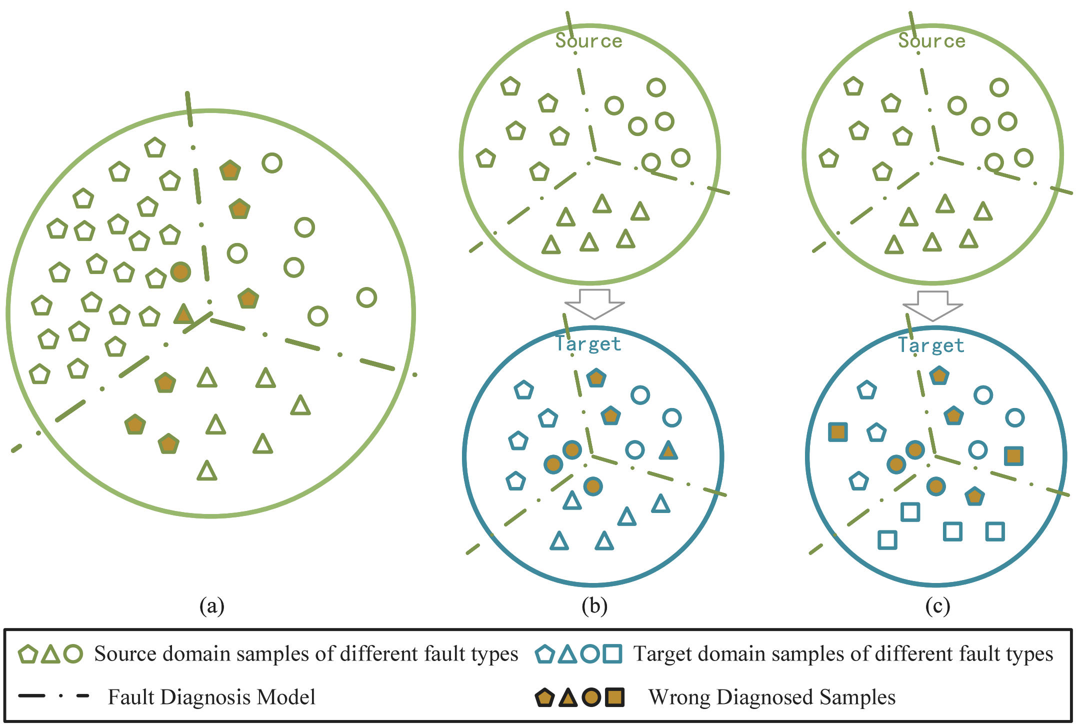


Fig. 10. The fault diagnosis of unbalanced small-size samples and transfer fault diagnosis problem (a) The fault diagnosis of unbalanced small-size samples and (b) Transfer fault diagnosis (c) Transfer fault diagnosis of unbalanced data.

condition of unbalanced number of samples. The imbalance of training data makes the knowledge learned by the model erroneous, so it is easy to make wrong determination. This causes the fault diagnosis of unbalanced small-size samples to become an urgent problem which needs to be overcome [87,91].

Based on the open-source code framework for fault diagnosis of rotating machinery released by Zhao et al. [31], the authors conduct fault diagnosis experiments of unbalanced small-size samples. Order argumentation and Z-score normalization are used to process data, and time-domain signals are taken as input. AE, RNN, CNN and GAN are used as different diagnosis networks, respectively. One-dimensional Resnet18 and BiLSTM are used to represent CNN and RNN respectively. ACGAN is used to directly obtain classification results, which stacks one-dimensional data into a two-dimensional matrix as network input. For more detailed experimental settings, please refer to the paper and open-source codes published by Zhao et al. [31]. This paper does not conduct comparative experiments on DBN. The main reason for this is that the training of DBN is significantly different from other networks, including one-by-one RBM greedy training, BP classifier training, and DBN overall parameter fine-tuning. Therefore, it is extremely difficult to find a reasonable standard to initialize the parameter settings used in these trainings. Most current DBN-based methods still require manual feature extraction and selection of raw signals. Although DBN is commonly used in fault diagnosis research of rotating machinery, there is no DBN in the open-source framework released by Zhao et al. and the training of DBN is significantly different from the rest of comparative networks [31]. We trained DBN according to the experiments of some papers and found that DBN is difficult to converge on the SEU dataset and lacks comparability with other comparative networks.

In this paper, a dataset of imbalanced small-size samples is constructed based on the Southeast University (SEU) gearbox dataset, which sets the ratio of training set to testing set to 8:2. The SEU dataset has been initially introduced in Section 2. Since the SEU dataset contains both bearing and gear data, it is used in this paper. Moreover, the SEU dataset has rich fault types, and involves two working conditions. Transfer fault diagnosis experiments can be performed, which can further verify the diagnosis ability of the model [31]. The construction method is given as follows. The testing set is unchanged, and the health data in the training set is unchanged. Each class has 82 training samples, and the fault samples are reduced by a certain proportion. To demonstrate the impact of imbalanced fault samples, 20 gearbox fault types (there are two working conditions, each involving five health states of bearings and gears) are randomly divided into four parts, and each part maintains a different proportion. The constructed imbalanced dataset and the fault diagnosis tasks of imbalanced small-size samples are shown in Tables 3 and 4. The ratio represents the ratio of the number of various samples to the number of healthy samples. 2, 7, 11, and 16 are the labels of health samples of bearings and gears under two

Table 3
Imbalanced small-size dataset A and fault diagnosis tasks.

Ratio / Task / Label	SI1	SI2	SI3	SI4	SI5
2,7,11,16	1.0	1.0	1.0	1.0	1.0
Other	0.02	0.1	0.2	0.5	1.0

Table 4
Imbalanced small-size dataset B and fault diagnosis tasks.

Ratio / Task / Label	SI6	SI7	SI8	SI9	SI10
2,7,11,16	1.0	1.0	1.0	1.0	1.0
0,1,8,10,12	0.06	0.1	0.2	0.5	1.0
3,4,5,6,9	0.04	0.08	0.12	0.16	0.2
Other	0.02	0.04	0.06	0.08	0.1

Table 5
Fault diagnosis results of imbalanced small-size samples (%).

Task	AE	RNN	CNN	GAN
SI1	25.71 ± 4.13	29.52 ± 3.46	56.33 ± 2.44	21.09 ± 0.36
SI2	28.48 ± 1.47	49.14 ± 0.36	67.57 ± 1.33	29.81 ± 2.34
SI3	30.43 ± 2.97	55.71 ± 1.84	83.29 ± 1.96	35.48 ± 1.59
SI4	41.81 ± 2.73	72.90 ± 2.18	99.38 ± 0.36	45.10 ± 3.34
SI5	58.57 ± 2.40	96.52 ± 0.78	99.90 ± 0.13	75.38 ± 0.64
SI6	33.10 ± 0.92	41.95 ± 2.27	63.67 ± 2.90	24.48 ± 1.99
SI7	33.19 ± 1.32	49.14 ± 1.41	68.52 ± 1.99	33.33 ± 1.91
SI8	31.95 ± 1.82	51.76 ± 2.51	73.95 ± 1.16	34.29 ± 2.53
SI9	30.05 ± 1.34	56.95 ± 2.41	76.43 ± 1.02	37.24 ± 1.25
SI10	39.33 ± 2.30	62.48 ± 1.47	81.10 ± 0.40	40.71 ± 2.24

working conditions, respectively. Two imbalanced datasets A and B are designed. The proportion of failure samples in dataset A is the same. The failure samples in dataset B are divided into three parts, and the number of each part is different.

The diagnosis results on several networks are shown in Table 5, which are the mean and standard deviation of the maximum diagnosis accuracy in five repeated experiments. According to the results, CNN has stronger feature learning ability in fault diagnosis of imbalanced small-size samples, especially in the condition of seriously imbalanced data. For instance, the corresponding diagnosis accuracy is much higher than the other ones in SI1 and SI6 tasks. The diagnostic accuracy fluctuation of CNN increases with the degree of imbalance, which is more regular than the other models. Unexpectedly, in SI6, SI7 and SI8 tasks, the widening gap in the number of samples between classes leads to a decrease in the diagnosis accuracy even when the total number of samples increases. The impact of class imbalance on AE is strong, which reflects the weak feature learning ability of the ordinary AE. Although the diagnosis ability varies, the diagnosis accuracy of each type of network decreases significantly with the increase of data imbalance and the decrease of sample size, which is consistent with existing research results. The training process of DatasetA and DatasetB on CNN is shown in Figs. 11 and 12 respectively. With the reduction of fault samples, the diagnosis accuracy is significantly reduced, and the convergence is also slower and unstable. The imbalance of various fault samples significantly increases the convergence difficulty of the model.

For fault diagnosis of imbalanced small-size samples, existing solutions mainly augment the dataset with high-quality data to balance the dataset. Commonly used generative models include AE and its variants and GANs. Existing methods mainly guide the network to generate high-quality samples by optimizing the loss function. For AE and RNN variants, the reconstruction loss is mainly improved. For GAN, the classification loss of the discriminator is improved. In a few existing studies, RNN variants such as GRU and LSTM are also used to generate auxiliary samples. Some hybrid generative models such as CVAE-GAN [197] have also been proposed. In addition, regularization mechanisms such as Dropout, BatchNorm, etc. are applied to the feature extraction network to reduce the requirement of data size on model training [128].

Table 6
The tasks of transfer fault diagnosis.

Task	Source	Target
TF1	20 Hz–0 V	30 Hz–2 V
TF2	20 Hz–0 V	20 Hz–0 V
TF3	30 Hz–2 V	20 Hz–0 V
TF2	30 Hz–2 V	30 Hz–2 V

Table 7
Results of transfer fault diagnosis (%).

Task	AE	RNN	CNN	GAN
TF1	56.10 ± 2.17	53.33 ± 2.95	54.19 ± 2.11	46.86 ± 1.63
TF2	56.67 ± 2.16	97.14 ± 0.58	100.0 ± 0.00	75.24 ± 2.96
TF3	52.95 ± 3.69	50.48 ± 1.84	50.29 ± 1.74	49.24 ± 0.72
TF2	59.62 ± 2.57	91.24 ± 0.54	100.0 ± 0.00	83.24 ± 1.66

4.1.2. Transfer fault diagnosis

Changes in conditions such as equipment and working conditions of rotating machinery generate new work scenarios. Due to the lack of labeled samples in new scenarios, it is necessary to apply models previously trained in related domains to new scenarios. However, models trained entirely on source-domain data often perform poorly in the target domain (as shown in Fig. 10(b)), which leads to the problem of transfer fault diagnosis. The diagnosis model needs to be able to overcome the data distribution difference between training set and testing set caused by various factors such as equipment and operating condition changes [27,28]. Transfer fault diagnosis of unbalanced data occurs when the source-domain data is unbalanced with the target-domain data. When the source domain and target domain contain different data categories, there is an imbalance in the label space, as shown in Fig. 10(c). This situation is closer to reality and more difficult to solve [173].

According to the models used in the fault diagnosis experiments of imbalanced small-size samples, this paper conducts transfer fault diagnosis experiments between different working conditions on the SEU dataset. Transfer fault diagnosis is applied to two operating conditions 20 Hz–0 V and 30 Hz–2 V appearing in the dataset. The fault types are divided into 10 types (5 types of bearings and gears respectively), and each type has 82 training samples. Tasks of transfer fault diagnosis are shown in Table 6. The transfer fault diagnosis results of several networks are shown in Table 7. For several networks except AE, the change of working conditions leads to a significant decrease in diagnosis accuracy and has a greater impact on RNN and CNN with strong feature extraction capabilities. For GAN, although its performance on the source domain is poor, working condition changes have low impact on it, which reflects the advantage of adversarial learning in transfer fault diagnosis. Surprisingly, the diagnosis accuracy of AE is not considerably affected by the change of working conditions, which confirms better generalization performance of AE. Possibly, the features extracted by AE are general. Although the generalization performance of AE is good, its diagnosis accuracy is still low.

The training process of CNN is shown in Fig. 13. The model that performed well in the original working conditions. When the model was used in other working conditions, the diagnosis accuracy dropped significantly, and the loss even showed an upward trend. Differences in data distribution caused by changes in operating conditions can considerably reduce the diagnosis performance of the model.

For transfer fault diagnosis, most of existing methods focus on applying some transfer learning and domain adaptation theories to enable DL models to overcome the data distribution shift caused by various factors such as equipment changes, operating condition changes, and even sensor location changes [176]. According to the discussion in Section 3, commonly used transfer techniques mainly include parameter transfer, discrepancy measure, and domain adversarial adaption. Several methods are briefly introduced as follows.

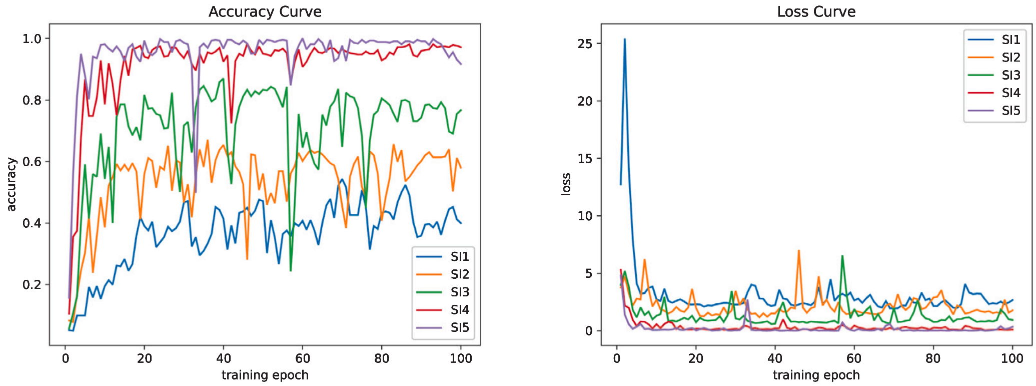


Fig. 11. CNN training on DatasetA.

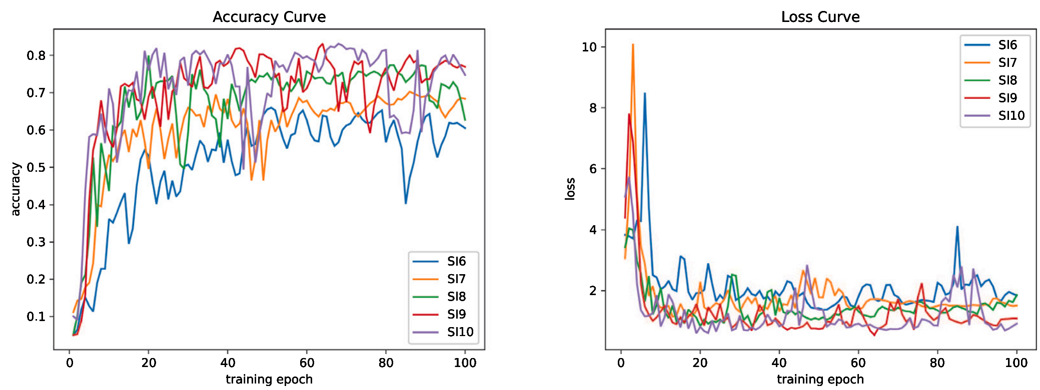


Fig. 12. CNN training on DatasetB.

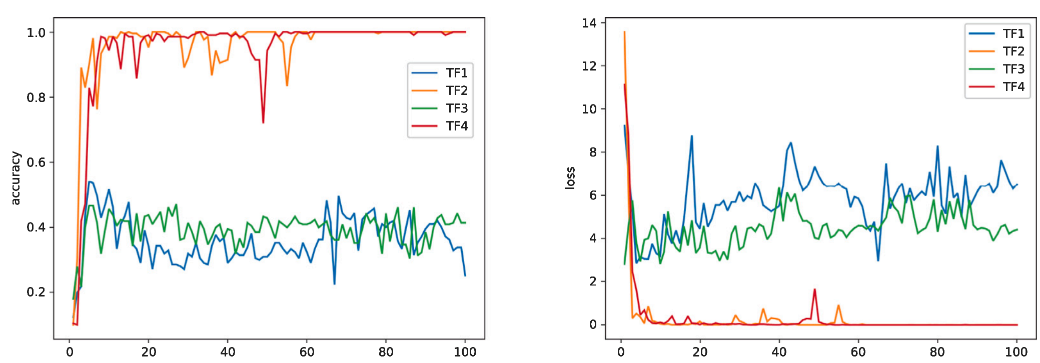


Fig. 13. The process of transfer fault diagnosis.

(1) Parameter transfer: The basic process of the parameter transfer method can be summarized as follows. Partial parameters of the model trained by the supervised training on labeled source-domain data are transferred to the target-domain model. The transferred parameters are considered as the part of the model responsible for extracting transferable features. The remaining task-specific parameters of the target-domain model are obtained by fine-tuning a small number of labeled samples in the target domain.

The application of this method in transfer fault diagnosis methods is common, and it exists in the DL-based IFDRM research. The general pattern is shown in Fig. 14. In some scenarios, good transfer performance can be achieved, but the need to label data in the target domain still makes this type of method agonizingly limited. Additionally, the number of labeled samples in the target domain for fine-tuning is not a deterministic factor, and the imbalance of these samples is also likely to lead to a decrease in diagnosis accuracy.

(2) Discrepancy measure: According to the idea of the method based on discrepancy measure, the distribution difference index between source-domain data and target-domain data is used to optimize network parameters. The network can extract the domain-invariant features. Therefore, the network can realize fault diagnosis according to the target-domain data. This process does not require labeled target-domain data. The statistical parameters used to measure the difference in feature distribution are directly calculated from the features extracted by the network. Typically, in the field of IFDRM, maximum mean discrepancy (MMD) [214] is often used as an evaluation indicator of distribution difference.

MMD maps the high-dimensional features of the two domains to the regenerated kernel Hilbert space through the mapping function,

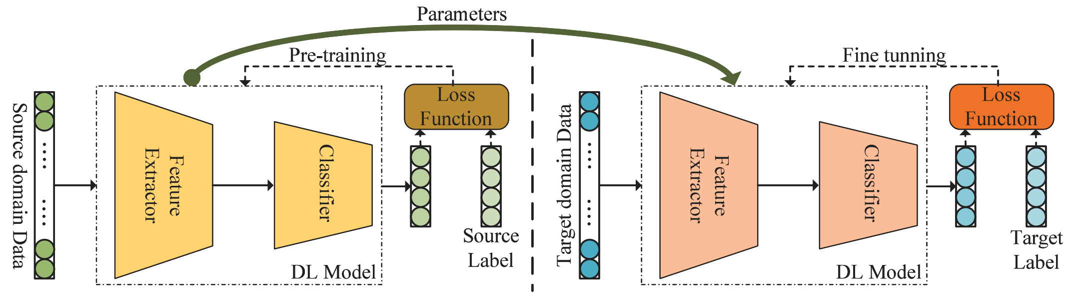


Fig. 14. The transfer fault diagnosis method based on parameter transfer.

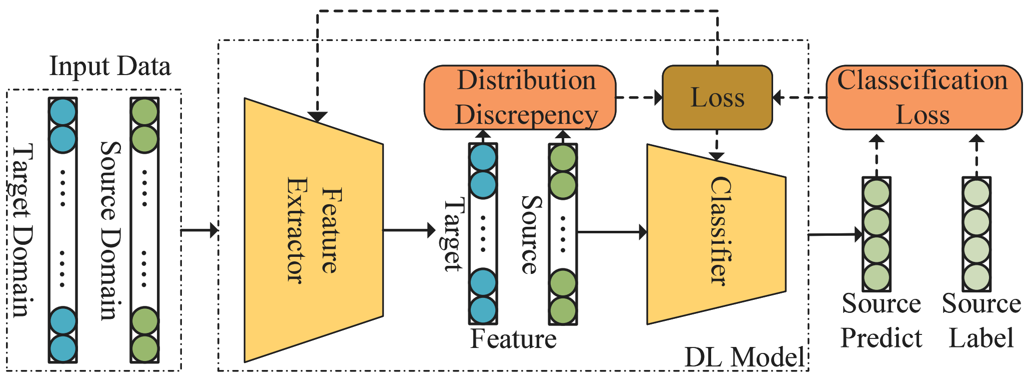


Fig. 15. The transfer fault diagnosis based on discrepancy measure.

and then obtains the distribution difference of the two domains by calculating the maximum average difference between source domain $X^s = \left\{x_i^s\right\}_{i=1}^{N_s}$ and target domain $X^t = \left\{x_j^t\right\}_{i=j}^{N_t}$ in this space. The calculation formula of MMD can generally be expressed as follows.

$$MMD_H = \left\| \frac{1}{N_s} \sum_{i=1}^{N_s} \kappa(x_i^S) - \frac{1}{N_t} \sum_{j=1}^{N_t} \kappa(x_j^t) \right\|_H^2 \tag{1}$$

where N_s and N_t are the number of samples in source domain and target domain respectively, H is reproducing kernel Hilbert space (RHKS), κ is a nonlinear mapping function that maps the original features to RKHS space. When MMD becomes smaller, the difference in data distribution also becomes smaller. In practical applications, in order to achieve good transfer performance, improved MMDs are used, such as joint MMD (JMMD) [215], MK-MMD [216], pseudo-categorized maximum mean discrepancy (PCMMD) [171] and weighted MMD (WMMD) [217]. Compared with the original MMD, these parameters can guide the network to learn domain-invariant features effectively. The general pattern of the fault diagnosis methods based on discrepancy measure is shown in Fig. 15.

In discrepancy measure-based methods, the calculated discrepancy indicator is often used as a part of the loss function, which is first multiplied by a decay coefficient and then added to the classification loss of the labeled source-domain data to create a loss function for guiding the optimization of the network. However, this type of method is not satisfactory enough in the face of data with complex composition and large distribution discrepancy. Although this transfer idea is easy to understand in theory, the distribution difference loss does not always perform well in the task of reducing feature distribution differences, due to the constraints of the gradient descent learning strategy of the network.

(3) Domain-adversarial adaptation: Domain-adversarial adaptation methods have been active in transfer fault diagnosis in recent years. The idea of domain adversarial neural network (DANN) [218] comes from GAN, which converts the identification of true and false input samples in GAN into identifying the extracted features from source domain or target domain. Additionally, a classifier is added to guide the feature extractor in learning the features of different types of faults. Compared with adding complex distribution difference loss and relying on network learning to gradually overcome feature distribution differences, domain-adversarial adaptation can take advantage of adversarial learning and powerfully guide the feature extractor to extract domain-invariant features that are difficult for the discriminator to distinguish. The general pattern of the IFDRM methods based on domain-adversarial adaptation is shown in Fig. 16.

Generally, for speed and load transfer, the difference between source-domain and target-domain data increases, the distribution difference increases, and the difficulty of transfer learning also increases. For sensors, the data collection method and collection location are the main influencing factors. For the transfer between devices, the influencing factors are the most complicated. The working environment of faulty components has changed considerably, and the collection method and working conditions (including speed and load) may be quite different, which results in the most difficult task of transfer fault diagnosis between devices. For the transfer fault diagnosis under the condition of unbalanced label space between source domain and target domain, Li et al. [173] proposed a conditional alignment mechanism guided by MMD loss to realize transfer fault diagnosis when the number of target-domain label categories is less than that of source domain. For the case of new fault types in target domain, Lv et al. [101] and Li et al. [99] proposed zero-shot classification methods for the occurrence of new fault types in the target domain. In general, there are relatively few research results on transfer fault diagnosis under the condition of unbalanced source and target domains.

4.1.3. Others

(1) For most of DBN, AE and RNN based IFD methods, effective data dimensionality reduction in the data preprocessing stage is still an important step [22,219]. Although some above-mentioned existing solutions also tried to use raw data, the dimension of input data in these solutions is much smaller than that of CNN-based methods, which has certain limitations for sensor data with high sampling frequency.

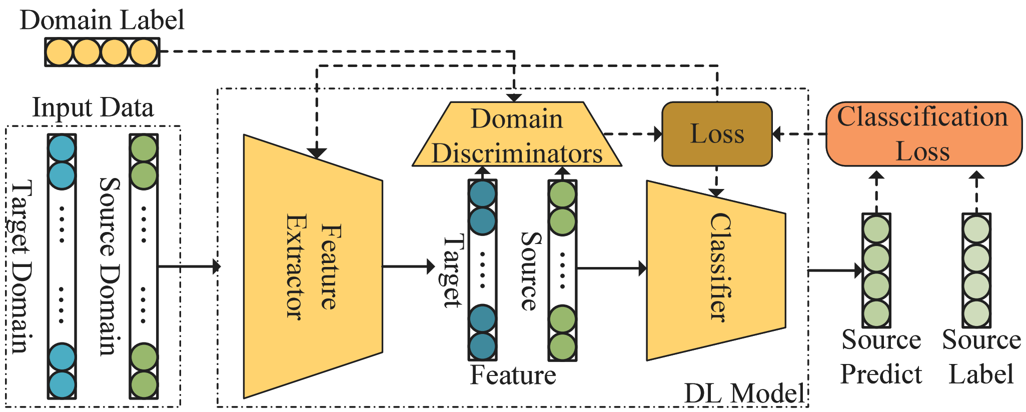


Fig. 16. Transfer fault diagnosis methods based on domain-adversarial adaptation.

Essentially, methods based on hand-extracted features rely on prior knowledge and expert experiences. How to overcome this dependence has always been a hot question.

To overcome the dependence on expert experiences and domain knowledge and avoid handcrafted and extracted features, the DLIFD methods perform simpler and more automated processing methods such as fast furious transform (FFT), short time furious transform (STFT), and wavelet transform (WT) on raw data, or directly use raw signals. Raw signals are most widely adopted in CNN-based methods, which mostly focus on building end-to-end diagnosis models and achieve excellent results. It is still an open question as to which processing method is the best one to contain and express fault information [22].

(2) In model construction, no matter what kind of DL model it is, there is no fixed method for determining the hyperparameters related to its specific structure such as the number of network layers, the number of neurons in each layer of DBN or AE, the size of the convolution kernel of CNN, and the convolution step size. This makes it difficult to obtain optimal results [76,81].

In the task of determining the specific structure of the DL model and other hyperparameters, researchers mainly use two types of methods. (i) Relying on experience to select the best hyperparameters through experiments within a certain range. This method is called the trial and error method. (ii) With the help of various optimization algorithms such as PSO [57] and genetic algorithm [59] (GA), hyperparameters are used as optimization targets, and diagnosis accuracy is used as a feedback condition to obtain optimal hyperparameters.

(3) In actual scenarios, besides the non-stationary and nonlinear characteristics of the vibration of complex rotating mechanical equipment such as planetary gearboxes, there is always noise in the signals that cannot be completely eliminated, which is mentioned in almost all of the literature. Therefore, eliminating the adverse impacts of noise has great significance to improve the diagnosis accuracy [74,78,220].

Faced with the unavoidable noise interference problem, existing methods mainly make improvements from the perspectives of data preprocessing and network model to suppress noise. In addition to traditional filtering methods, signal transformation methods such as FFT, WT, and S-transform [89] are used to transform the original signals into other domains, which are also considered to have a certain effect on reducing the impact of noise. The hand-designed feature set is also considered to have a certain effect on noise containment. Well-designed feature sets can often weaken the impact of noise. However, this method has an obvious shortcoming. It is highly dependent on the professional experiences and knowledge of researchers. In contrast, making improvements on the network structure does not require extensive denoising knowledge. The gate structure of DAE [118] and LSTM [126] is considered to be effective in reconstructing the denoised signals. In CNN-based methods, wide convolution kernels are also considered beneficial to suppress high-frequency noise interference in the input data [178]. In addition, in the model training stage, incorporating random noise with a certain SNR into the training samples is considered to effectively enhance the model's anti-noise ability. Embedded model has become a popular DL-based diagnosis model integrating various models that can overcome different problems and effectively accomplish diagnosis tasks [110,113,118,126,221].

(4) DL-based fault diagnosis models have the "common problems" of deep learning algorithms such as gradient disappearance, slow convergence, and overfitting, which adversely affect the feature extraction and classification process [53,57].

In the face of the "common problems" in deep learning, corresponding improvement strategies have been introduced to DL. The integration of the most commonly used optimization strategies such as adaptive dynamic learning rate, Dropout, BatchNorm and NM and various DL-based fault diagnosis models overcomes these "common problems" to a certain extent. In addition, some classic optimization network structures, such as residual structure as shown in Fig. 17(a) and dense connection structure as shown in Fig. 17(b) are used to improve the feature extraction capability of the network, which are mainly reflected in the methods based on CNN and GAN [222].

(5) In addition to the above problems, the researchers also found that in the process of feature extraction of DL models, some factors adversely affect the fault diagnosis results, such as the time–frequency domain signals not fully expressing the fault information, the multi-scale features in vibration signals are ignored, CNN causes the loss of partial information during the downsampling process, the time correlation of signals is ignored, and the long-distance dependence of signals is not preserved, the sensor information of different orientations is not effectively combined and utilized. In conclusion, these new studies point out that in some methods, some important information or features of vibration signals cannot be effectively extracted by various DL models, which causes the features to have some special defects and reduces diagnosis accuracy.

Faced with the problem that the extracted features have special defects, existing research mainly makes improvements from two aspects, data and network structure. Researchers apply signal processing techniques and feature fusion techniques to enable models to learn multi-scale features and multi-sensor information [41]. Many researchers use preprocessed multiple inputs integrated with multi-branch diagnosis models, fuse the features of multiple branches, and let the model extract complementary information from the fused features [56,151,152,162,167,178,223]. The model structure of multiple branches is often similar, and different features are extracted from different inputs. A common multi-branch and feature fusion structure is shown in Fig. 17(c). Faced with the problem of the loss of temporal correlation of signals, RNN and its variants are considered to be able to effectively preserve the temporal correlation of features because of their unique information flow transmission [114,115]. For CNN's ignorance on long-range dependencies during feature extraction, dilated

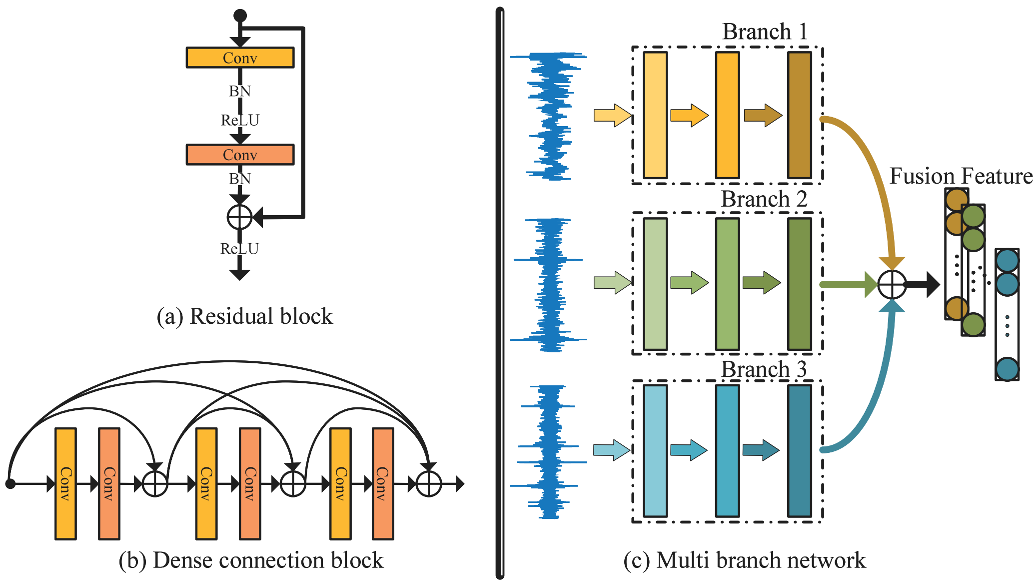


Fig. 17. Several structures that enhance network feature extraction capabilities (a) residual structure (b) densely connected structure (c) multi-branch and feature fusion structure.

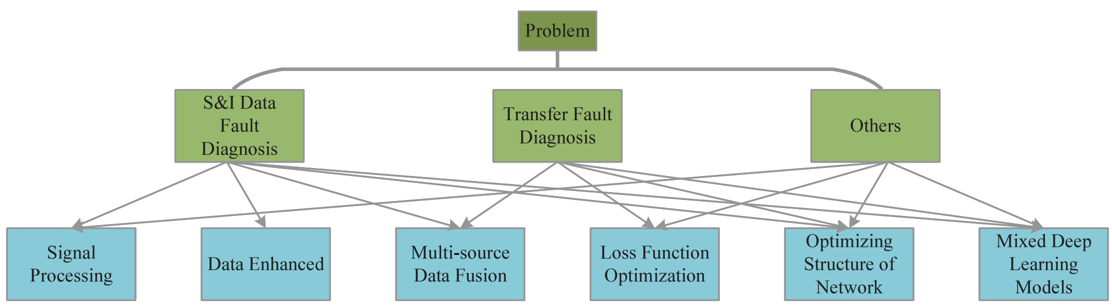


Fig. 18. The relationship between problems and methods.

convolution operations are considered to capture long-range dependencies [166]. For the problem that partial information in the samples is lost due to the continuous downsampling operation of CNN, residual structure, densely connected structure and cascade structure are considered to be beneficial to supplement the lost information [145].

4.1.4. Problem summary

Existing literature proposes a wealth of improvement methods for many problems, and these methods have certain common characteristics. Through the above discussion of existing problems and methods, existing methods can be summarized as data-level and network-level methods. The data-level methods are mainly realized through rich signal processing methods, data enhancement methods such as data expansion, and multi-source data fusion. The network-level methods are mainly realized by optimizing network structure and improving loss function. As shown in Fig. 18, these methods are present in research on various problems.

4.2. Comparison of DL-based IFDRM methods

Table 8 compares the advantages and disadvantages of IFDRM methods based on various DL models.

4.3. Future research trends

The previous discussion summarizes the problems and existing solutions of DL-based IFDRM methods. Some problems can be well solved, and some problems are still insurmountable. To this end, this section proposes some key future research directions.

4.3.1. Data preprocessing

In the methods based on DBN, AE and RNN, many complex feature set production methods have been proposed, including time-domain information, frequency-domain information, and non-time–frequency domain information. But so far, none of the preprocessing methods is considered to be the most effective and most capable of containing fault information. Especially for methods based on one-dimensional input data, excellent data dimensionality reduction preprocessing methods are still a research hotspot. For CNN-based methods, perhaps the original signals can well exploit the potential of CNN, but the proper preprocessing can also enhance data training and reduce the learning difficulty of CNN. For different DL models, data preprocessing requirements are also significantly different. Therefore, it is meaningful to develop data preprocessing methods suitable for different models to ensure the quality of input data. More importantly, effective data dimensionality reduction can considerably reduce the demand for hardware equipment and improve efficiency of fault diagnosis.

4.3.2. Fault diagnosis with small and imbalanced data

In addition to class imbalance and label space imbalance, there are some special cases such as One-shot and Zero-shot learning for fault diagnosis with imbalanced small-size data. Under these conditions, the normal learning conditions required by DL models cannot be guaranteed, which makes it difficult for DL models to learn useful knowledge and they fail to achieve satisfactory fault diagnosis accuracy. In actual engineering scenarios, the collected data, especially the data of key components, is far different from most laboratory datasets, and the amount of the collected data is extremely unbalanced, making the

Table 8
Comparison of advantages and disadvantages of DL models in IFDRM.

Models	Advantages	Disadvantages
DBN	It is easy to expand (such as convolutional DBN) and has good flexibility. It can effectively handle unlabeled data and avoid overfitting and underfitting problems.	It is difficult to deal with large-size original data and two-dimensional data. Data preprocessing is complicated. The convergence speed is slow. The classification accuracy is low. The input data needs to be translation invariant.
AE	The reconstruction error can be used to realize unsupervised training. The variants are rich and the application is flexible. It can be used as a generative model to realize data compensation.	It is difficult to deal with large-size two-dimensional data. The convergence speed is slow. The classification accuracy is low. The feature extraction ability is weak. The input data needs to be translation invariant. The data preprocessing is complicated.
RNN	Processing time series has the unique advantage of preserving the temporal correlation of input data. It can also be used as a generator to generate auxiliary samples.	The fault feature learning ability is weak, and it is often combined with other models to extract features. The amount of parameters is large, and gradient disappearance or gradient explosion problems are prone to occur. It is difficult to process two-dimensional data.
CNN	Strong data compatibility; strong feature extraction ability; less model parameters than fully connected networks; flexible and changeable structure.	The problem of gradient disappearance is prone to occur. There is a problem of information loss, and the quality of extracted features is affected; The training time is long.
GAN	It has strong generation ability and is a powerful data compensation tool. It has rich variants and can achieve fault classification together.	The training process is unstable. It is not suitable for processing discrete data. The application structure in IFD is relatively limited.

training of DL-based models difficult. Although data augmentation with generative models can improve the class imbalance problem, data synthesized with only a few samples is still insufficient. As a key problem, how to use few-shot learning to solve the imbalance problem remains to be further explored. In addition, zero-shot learning helps to achieve diagnosis in the presence of unknown fault types in the target domain, and the integration of zero-shot learning theory and IFD is a valuable research direction.

4.3.3. Transfer fault diagnosis

In the current most popular transfer fault diagnosis tasks, domain adaptation theory is most commonly used, but the determination criteria about domain boundary are not fixed and are different in various transfer scenarios. Despite the rapid development of transfer fault diagnosis methods based on domain adaptation, the limitations of their use are still a problem. How to improve the generalization ability of diagnosis models between different working conditions and between different devices continues to be the focus of future research. It is meaningful to realize transfer fault diagnosis under the condition of unbalanced label space between source domain and target domain, which is closer to the actual situation, but there are few related studies. The methods based on transfer learning have made a breakthrough in fault diagnosis under variable working conditions. However, there are still some challenges that need to be discussed further [1]: (1) The networks based on transfer learning algorithms vary, making it difficult to directly compare the corresponding results of different networks. Therefore, the influence of different networks has not been studied in depth. (2) If the assumptions related to both source and target domains are invalid, the transfer learning-based algorithms may perform negative transfer using the diagnosis knowledge of source domain, thereby reducing the transfer performance of the corresponding models.

Many TFD methods essentially achieve fault diagnosis by enhancing the generalization performance of the model. However, there is little research on fault diagnosis dedicated to domain generalization. Domain generalization is different from domain adaptation. When the target-domain data is completely unavailable, only the source-domain data is used without relying on the labeled or unlabeled target-domain data to train a diagnosis model that can perform well in the target domain. This is an attractive research direction, but it is also extremely difficult. The effectiveness of the proposed TFD methods is mostly limited to small-scale changes in operating conditions. For cross-device transfer scenarios, the realization of domain generalization is difficult.

4.3.4. Interpretability of DL models

DL-based diagnosis models are constructed through experiment after experiment rather than strictly theoretical background. The learning of model parameters relies on good initial values rather than strictly derived results. The interpretability of DL-based models can help users understand how diagnosis models can learn useful fault knowledge from sensor data. As a major limitation of the application of DL in IFDRM, DL methods operate as “black boxes” and are not interpretable, which provides no insight into how and why they are able to make final decisions. The “black box” effect of deep learning makes many key problems difficult to explain theoretically. Unlike some fields that require less precision and rigor, wide fluctuations in the fault diagnosis accuracy of key components are not allowed in industrial applications. The interpretability of DL-based models is crucial for DL-based IFD methods to play an importance role in industrial scenarios, and is a cutting-edge research in the field of deep learning.

5. Conclusion

IFDRM is an important guarantee for the normal operation of rotating machinery and is a research hotspot in recent years. This paper reviews recently published DL algorithms in RMIFD and summarizes existing methods from the perspective of DL algorithm types, such as DBN, AE, RNN, CNN, and GAN categories. First, the basic principles of several types of DL algorithms are introduced, and then existing methods are introduced from the research motivation and solutions. The methods based on various DL algorithms show different characteristics, and their application characteristics are summarized respectively. This paper summarizes the main problems faced by existing methods into fault diagnosis of imbalanced small-size samples and transfer fault diagnosis, and conducts experiments on open-source frameworks and datasets to illustrate the existence of the related problems. Existing methods have been improved from data preprocessing, model structure and loss function respectively. Although many issues have been improved, there are still many that need to be addressed. Therefore, some issues that still need to be solved and future research hotspots are summarized at the end of this paper.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zhiqin Zhu reports financial support was provided by Chongqing University of Posts and Telecommunications. Zhiqin Zhu reports a relationship with Chongqing University of Posts and Telecommunications that includes: employment and funding grants.

Data availability

The public datasets are used.

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