Deep Transfer Learning for Bearing Fault Diagnosis: A Systematic Review Since 2016

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Abstract—The traditional deep learning-based bearing fault diagnosis approaches assume that the training and test data follow the same distribution. This assumption, however, is not always true for the bearing data collected in practical scenarios, leading to significant decline to fault diagnosis performance. In order to satisfy this assumption, the transfer learning concept is introduced in deep learning by transferring the knowledge learned from other data or models. Due to the excellent capability of feature learning and domain transfer, deep transfer learning methods have gained widespread attention in bearing fault diagnosis in recent years. This article presents a comprehensive review of the development of deep transfer learning-based bearing fault diagnosis approaches since 2016. In this review, a novel taxonomy of deep transfer learning-based bearing fault diagnosis methods is proposed from the perspective of target domain data properties divided by labels, machines, and faults. By covering the whole life cycle of deep transfer learning-based fault diagnosis and discussing the research challenges and opportunities, this review provides a systematic guideline for researchers and practitioners to efficiently identify suitable deep transfer learning models based on the actual problems encountered in bearing fault diagnosis.

Index Terms—Bearing fault, deep transfer learning, fault diagnosis

I. INTRODUCTION

Bearing, a key tribological part used to reduce friction and enable elements to run smoothly, is widely applied in almost all kinds of rotating machinery, such as transmission, steel rolling mills, wind turbines, high-speed train etc. The normal operation of rotating machinery is highly dependent on the health state of bearings. Compared with other mechanical elements, bearing is prone to faults due to prolonged exposure to harsh working conditions, such as high temperature, high rotational speed, and high load. According to statistics, about 45-55% of mechanical faults were caused by bearing failure, reflecting the importance and necessity of bearing fault diagnosis [1–8]. In order to reduce the maintenance cost and avoid casualties, it is necessary to diagnose the faults timely and

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accurately before the occurrence of immeasurable loss [9–13]. With the advanced development of artificial intelligence and sensor technologies, many intelligent bearing fault diagnosis approaches have been proposed in the past few years (with examples shown in [14–21]), providing significant improvements in this field. According to current research, the existing intelligent fault diagnosis methods can be roughly divided into three categories: conventional machine learning methods, deep learning methods, and transfer learning methods [22].

Conventional machine learning-based fault diagnosis approaches typically include three main steps: data collection, feature extraction, and fault classification. In data collection step, various sensors, such as vibration, current, temperature, and acoustic emission, are applied to collect raw data reflecting bearing health state. In feature extraction step, the data attributes are analyzed and the features are manually selected and extracted based on predefined formulas designed from expert knowledge [23–30]. This non-automatic feature extraction step may bring in irrelevant or redundant features from data that do not contribute to the accuracy of classification model. In fault classification step, the mapping relationship between features and faults is established using intelligent methods, including but not limited to decision tree [31], support vector machine [32], k-nearest neighbor [33], artificial neural network [34] and hidden Markov model [35].

With the advent of the Internet of Things, an unprecedented volume of data can be acquired easily, providing more fault-related information than ever before and boosting the accuracy of fault diagnosis [22]. Furthermore, the conventional machine learning-based fault diagnosis methods rely on the manual selection of valuable features for fault classification, but such a labor-intensive approach is time-consuming with massive data. In order to construct accurate fault diagnostic models and minimize the cost of manual feature extraction, deep learning methods are proposed to directly construct the mapping between fault signal and fault category. The deep learning-based fault diagnostic models can automatically learn fault features from input data and output health state without a priori knowledge. The typical deep learning models include but are not limited to convolutional neural network (CNN) [14, 36, 37], recurrent neural network [38], restricted Boltzmann machine [39], auto-encoder [40, 41], deep belief network [42], and their variants.

Remarkable success has been achieved in deep learning-based fault diagnosis in the past few years, but there are still two major issues to be considered: data distribution and data availability. Firstly, deep learning models assume that the
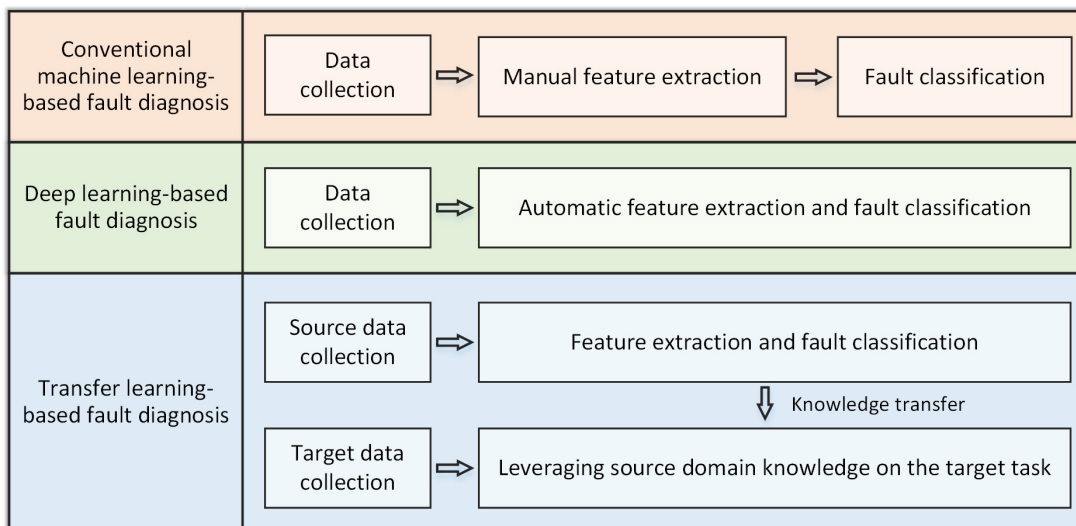
Fig. 1. The differences among conventional machine learning-based, deep learning-based and transfer learning-based fault diagnosis methods.

training and test data follow the same distribution. However, the working conditions such as loads and rotational speeds vary significantly according to different tasks in practical scenarios. Therefore, the distribution of test data collected from different working conditions is different from that of training data. In addition, if the test data are collected from different equipment, the fault diagnosis accuracy of deep learning models may drop significantly even if the fault types are the same [43–47]. Secondly, the performance of deep learning models mainly relies on the amount of labeled data to tune the model weights and biases. However, it is time-consuming and laborious to collect and label a large amount of fault data. In addition, it is not recommended to keep machines working under faulty conditions for data collection, which may decrease the equipment lifespan and increase the risk of casualties and property loss [22, 47]. If the data collection and labeling problems in different working conditions cannot be properly addressed, the general performance of deep learning-based fault diagnosis models cannot be guaranteed.

Transfer learning, introduced in 1995 to deal with life-long learning problems by reusing previous knowledge, relaxes the restriction that training and test data must follow the same distribution [46, 48]. As a promising method to leverage the knowledge learned from different but related tasks to tackle new problems, the idea of transfer learning is inspired by human learning mechanism to reuse the knowledge or skills summarized from tasks in other fields. For example, if one has learned how to ride a bicycle, then the skills of riding a bicycle will help in riding a motorcycle. The core idea of transfer learning is to find the shared characteristics of two or several correlated but not identical learning tasks and apply the shared knowledge to tackle new problems [49, 50]. In practical bearing fault diagnosis scenarios, the amount of normal data collected from bearing is usually far more than the amount of fault data, because it is usually prohibited by regulations to operate practical machines with faulty bearing for long time. Such an insufficient fault data problem can significantly reduce

the diagnostic performance of deep neural networks [51–54]. Therefore, it is crucial to introduce transfer learning to resolve the challenge of insufficient data. The differences between transfer learning and the above-mentioned fault diagnosis methods are shown in Fig. 1. In transfer learning-based fault diagnosis, the diagnostic model will firstly be pre-trained with source domain data and task, then the learned knowledge such as fault features or model parameters can be reused for the target domain fault diagnosis task.

To summarize the existing research works of transfer learning and intelligent fault diagnosis, comprehensive reviews have been conducted in recent few years. Pan et al. [48] and Weiss et al. [55] presented very detailed surveys in transfer learning in 2009 and 2016 respectively and provided precise definitions of transfer learning which are still widely used by other researchers. Zhuang et al. [56] surveyed more than forty homogeneous transfer learning methods to give readers a comprehensive and intuitive overview on transfer learning. For intelligent fault diagnosis, Liu et al [57] reviewed the applications of artificial intelligence algorithms in rotating machinery fault diagnosis in 2018, mainly focusing on conventional machine learning methods. To reflect the state-of-the-art methods in intelligent fault diagnosis, Zhang et al. [58] conducted a comprehensive review on the applications of conventional machine learning algorithms and state-of-the-art deep learning algorithms on bearing fault diagnosis, in which the classification accuracies of different deep learning algorithms were compared on Case Western Reserve University open access bearing dataset to provide readers with an intuitive insight. Lei et al. [22] systematically reviewed the development of intelligent fault diagnosis from the cradle to the bloom, and classified the research into three phases: traditional machine learning-based, deep learning-based and transfer learning-based intelligent fault diagnosis. In 2019, Zheng et al. [59] presented the first review on knowledge-based cross-domain fault diagnosis, classifying the existing research into instance re-weighting methods, feature transfer

methods, classifier adaptation methods, deep learning-based methods and adversarial-based methods. Li et al. [44] reviewed the applications of transfer learning on fault diagnosis in recent years and classified the existing research into four main categories, including transfer component analysis, joint distribution adaptation, deep adaptation network, adversarial domain adaptation. Yan et al. [60] provided a review on knowledge-based rotary machine fault diagnosis, and divided all methods into four parts by specific problems: transfer between multiple working conditions, locations, machines, and fault types. Zhao et al. [61] focused on unsupervised deep transfer learning on bearing fault diagnosis and provided baseline accuracy of widely used transfer learning methods on bearing and gearbox datasets. Li et al. [62] classified the current research on transfer learning-based fault diagnosis into four application scenarios: generalization performance improvement, partial domain fault diagnosis, emerging fault detection and compound fault decoupling.

Although previous reviews have summarized the remarkable achievements, most of the reviews divide the research problems from the perspective of the methodology, instead of the perspective of data in practical applications such as bearing fault diagnosis. Aiming to provide an appropriate suggestion on transfer learning method selection for researchers and practitioners, the authors reviewed the research progress of deep transfer learning-based bearing fault diagnosis since 2016, classified the publications in this topic from the perspective of target domain data properties, and provided a comprehensive analysis and discussion on the widely used deep transfer learning methods. The contributions of this survey to bridge the gap in the current literature are summarized as follows:

1) This review focuses on the development of deep transfer learning on bearing fault diagnosis in recent six years, and offers a systematic guideline for researchers in bearing fault diagnosis. By covering the whole life cycle of deep transfer learning including source domain data selection and transfer learning model selection, this works allows readers to systematically grasp the general steps of deep transfer learning-based bearing fault diagnosis and its research advance.

2) This review provides a novel taxonomy of deep transfer learning on bearing fault diagnosis from the perspective of the property of target domain data, which can help researchers and practitioners efficiently choose suitable deep transfer learning models based on the actual problems encountered in fault diagnosis.

3) This review provides a systematically comparative analysis on the widely used deep transfer learning algorithms from six criteria. In addition, the future works, including transferability assessment, transfer with distinct labels, transfer under abnormal data quality, multi-source transfer, incipient fault diagnosis and novel applications in transfer between different machines, are also discussed in this paper.

The rest of this review is organized as follows. An introduction to the definitions and fault diagnosis procedure using transfer learning is provided in Section II. The commonly used source domain datasets on bearing fault diagnosis are introduced in Section III. In Section IV, the deep transfer learning-based fault diagnosis methods since 2016 are explained in

detail from the perspective of target domain data properties divided by labels, machines, and faults. Following on from Section IV, four kinds of typical transfer learning methods are qualitatively analyzed in Section V. In Section VI, the challenges and opportunities in existing methods are provided and discussed. Finally, the conclusion is presented in Section VII.

II. DEFINITIONS AND FAULT DIAGNOSIS PROCEDURE

Before reviewing the development of deep transfer learning in bearing fault diagnosis, the definitions and diagnosis procedures need to be introduced and explained in detail to provide a clear overview.

A. Definitions and Notations

To maintain the consistency with other surveys, the definitions and notations of transfer learning are provided here with references to two surveys in [48] and [55]. Transfer learning involves two main concepts: domain and task. A domain $\mathcal{D}$ can be defined by two components: a feature space $\mathcal{X}$ and a marginal probability distribution $P(\mathbf{X})$, where $\mathbf{X}$ refers to a specific learning sample $\mathbf{X} = \{\mathbf{x}|\mathbf{x}_i \in \mathcal{X}, i = 1, \ldots, n\}$, n is the number of feature vectors and $\mathbf{x}_i$ represents i^{th} feature vector. For bearing fault diagnosis, $\mathcal{X}$ is the space of fault features, $\mathbf{X}$ is a sampled signal, and $\mathbf{x}_i$ refers to the ith faulty feature vector.

For a given domain $\mathcal{D} = \{\mathcal{X}, P(\mathbf{X})\}$, a task $\mathcal{T}$ can be represented by $\mathcal{T} = \{\mathcal{Y}, f(\cdot)\}$, where $\mathcal{Y}$ is a label space and $f(\cdot)$ is a predictive function. Predictive function $f(\mathbf{x}_i)$ is a learner to predict fault labels by learning the latent relation between the input and output from data and label pairs $\{\mathbf{x}_i, y_i | \mathbf{x}_i \in \mathcal{X}, y_i \in \mathcal{Y}\}$, where $\mathbf{x}_i$ and y_i denote the ith feature vector and faulty label respectively. From a probabilistic point of view, $f(\mathbf{x})$ can also be denoted by $P(y|\mathbf{x})$.

In transfer learning, the domains are usually divided into source domain and target domain respectively. According to the definitions above, the source domain data can be represented as $D_s = \{(\mathbf{x}_s, y_s) | \mathbf{x}_{s_i} \in \mathcal{X}_s, y_{s_i} \in \mathcal{Y}_s, i = 1, \ldots, n\}$, where $\mathbf{x}_{s_i}$ and y_{s_i} refer to the feature vector and corresponding faulty label respectively, and n is the number of source samples. Equally, target domain data can be represented as $D_t = \{(\mathbf{x}_t, y_t) | \mathbf{x}_{t_i} \in \mathcal{X}_t, y_{t_i} \in \mathcal{Y}_t, i = 1, \ldots, m\}$, where $\mathbf{x}_{t_i}$ and y_{t_i} refer to the feature vector and corresponding fault label respectively, and m is the number of target samples. In most cases, the number of source samples is much larger than the number of target samples, i.e. $n \gg m \geq 0$. By the same token, the source task is represented as $\mathcal{T}_s = \{\mathcal{Y}_s, f_s(\cdot)\}$ and target task is represented as $\mathcal{T}_t = \{\mathcal{Y}_t, f_t(\cdot)\}$, where $\mathcal{Y}_s$ and $\mathcal{Y}_t$ refer to the source and target label spaces respectively, and $f_s(\cdot)$ and $f_t(\cdot)$ refer to the source and target predictive functions respectively. Furthermore, if the target label is inaccessible, the target domain data is represented as $D_t = \{\mathbf{x}_{t_1}, \mathbf{x}_{t_2}, \ldots, \mathbf{x}_{t_m}\}$, and the target task is represented as $\mathcal{T}_t = \{f_t(\cdot)\}$.

Based on the above definitions and notations, the transfer learning for bearing fault diagnosis is illustrated in Fig. 2 and can be defined as follows:
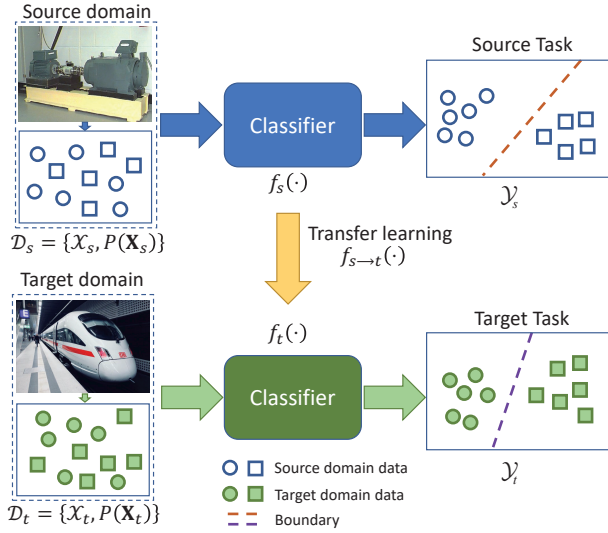
Fig. 2. An illustration on transfer learning-based fault diagnosis.

Transfer learning: given a source domain $\mathcal{D}_s$ with corresponding source fault diagnosis task $\mathcal{T}_s$, and target domain $\mathcal{D}_t$ with corresponding target fault diagnosis task $\mathcal{T}_t$, the transfer learning for bearing fault diagnosis aims to learn a mapping relationship $f_{s\longrightarrow t}\left(\cdot\right)$ to minimize the faulty feature difference by leveraging the faulty feature gained from source domain $\mathcal{D}_s$, and improve the target fault diagnosis function $f_t\left(\cdot\right)$, where $\mathcal{D}_s \neq \mathcal{D}_t$ or $\mathcal{T}_s \neq \mathcal{T}_t$.

B. Diagnosis Procedure of Deep Transfer Learning for Bearing Fault Diagnosis

This review focuses on the development of deep transfer learning in bearing fault diagnosis and provides a new taxonomy from the perspective of the property of target domain data. When researchers and practitioners encountered with cross-domain bearing fault diagnosis problems, the general procedure of bearing fault diagnosis based on transfer learning can be categorized into two steps: 1) source domain data selection and preprocessing; 2) transfer learning method selection. The overall steps of transfer learning for bearing fault diagnosis are shown in Fig. 3.

1) Source Domain Data Selection and Transformation: The outstanding performance of traditional deep learning algorithms highly relies on sufficient labeled data. However, the labeling process is time-consuming and labor-intensive; it is also hazardous to collect fault data with faulty bearings due to the risk of property loss and casualties. Fortunately, the shared knowledge between the source and target domains can be utilized by transfer learning to resolve such a challenge. However, if there is no common feature between the source and target domains, the knowledge transfer cannot provide a positive impact in transfer learning, eventually affecting the target predictive function performance. Therefore, it is of great importance and high priority to select an appropriate source dataset for the target task.

Seven commonly used open-source bearing fault datasets are introduced in this review, covering vibration, current, and temperature signals to provide researchers with auxiliary data to select from. These datasets are categorized into two groups according to the occurrence of faults: seeded fault dataset and run-to-failure dataset. Seeded fault data are collected from test rigs with various seeded fault components, and run-to-failure data denote that the faults are collected from the accelerated degradation experiments.

Although deep learning algorithms can realize "end-to-end" fault diagnosis, it is not efficient to directly feed the complex raw data into the training model [63]. The data transformation can provide alternative data properties by transforming the representations of raw signal, boosting the accuracy of fault diagnosis [64–66]. Time domain analysis [22, 67], frequency domain analysis [68–71] and time-frequency domain analysis [72–77] are widely used in fault diagnosis. In addition, image analysis is also popular in deep transfer learning fault diagnosis field. Recent studies showed that the image datasets are helpful in improving the performance of CNN networks on bearings fault diagnosis problems [75, 76, 78–80]. By converting one-dimensional time-series signals into two-dimensional grayscale [80–83] or RGB images [79, 84], researchers applied the pretrained CNN structure using large-scale image datasets such as ImageNet [85] for bearing fault diagnosis. Some researchers also applied FFT to convert the time domain data into frequency domain first, then transformed into two-dimensional spectral images [86–88] for bearing fault diagnosis.

2) Transfer Learning Method Selection: Different from previous reviews, in this review, a novel taxonomy from the perspective of the property of target domain data is presented to guide researchers and practitioners to efficiently identify suitable deep transfer learning methods based on the actual problems encountered in fault diagnosis. The taxonomy is based on three considerations: inductive or transductive transfer learning, transfer between different or same machines, transfer between different or same faults, as shown in Step 2 in Fig. 3.

The selection of transfer learning method depends on label availability in the source and target domains, and is generally divided into three categories: inductive transfer learning, transductive transfer learning, and unsupervised transfer learning [48]. In inductive transfer learning, the labels are available in both source and target domain data, i.e., $D_s = \{(\mathbf{x}_{s_1}, \mathrm{y}_{s_1}), \ldots, (\mathbf{x}_{s_n}, \mathrm{y}_{s_n})\}$ and $D_t = \{(\mathbf{x}_{t_1}, \mathrm{y}_{t_1}), \ldots, (\mathbf{x}_{t_m}, \mathrm{y}_{t_m})\}$, where n and m are the number of source and target domain samples respectively. Furthermore, inductive transfer learning is divided into two sub-cases: supervised transfer learning where all the target domain data are labeled and semi-supervised learning where few target domain data are labeled and the remaining large amount of data are unlabeled. In transductive transfer learning, the source domain labels are available, but the target domain labels are unavailable, i.e., $D_s = \{(\mathbf{x}_{s_1}, \mathrm{y}_{s_1}), \ldots, (\mathbf{x}_{s_n}, \mathrm{y}_{s_n})\}$ and $D_t = \{\mathbf{x}_{t_1}, \ldots, \mathbf{x}_{t_m}\}$. Since leveraging the labeled source datasets to provide inheritable faulty characteristics for target diagnosis task is a popular approach in transfer learning-based fault diagnosis, there is no related research, to the best of the authors' knowledge, on unsupervised transfer learning in
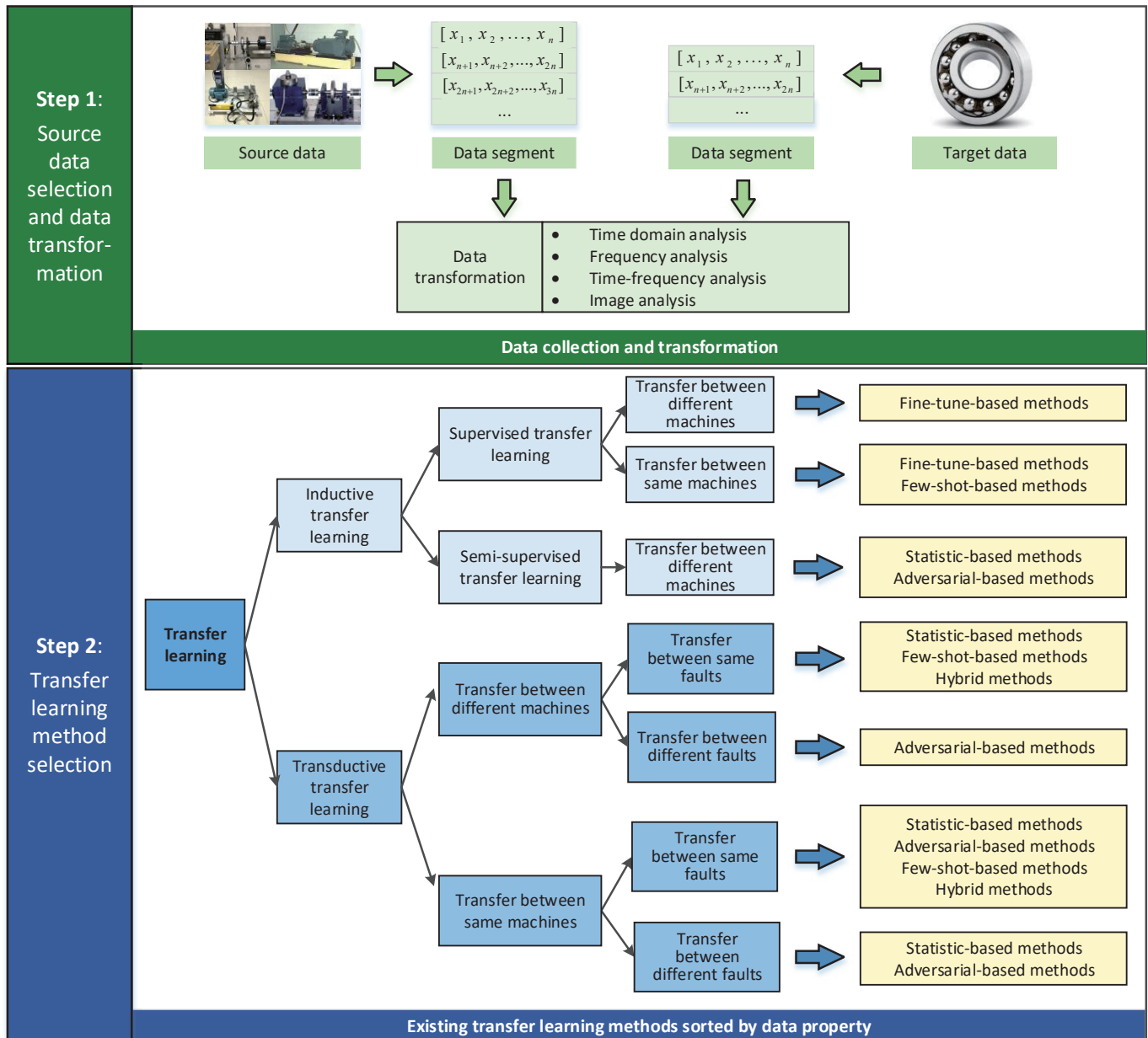
Fig. 3. Diagnosis procedure of deep transfer learning for bearing fault diagnosis.

bearing fault diagnosis, thus unsupervised transfer learning is not considered in this review.

In practice, generating faulty data from experiment platform and leveraging historical faulty data collected from other machine types are feasible approaches to address cross-domain bearing fault diagnosis problems, as the experimental data and historical data contain inheritable features. However, as the time and frequency domain characteristics of bearings are greatly affected by machine types and structures, the feature distributions of different machines can be very different. Therefore, transfer between same or different machines should be regarded as two totally different application scenarios.

In addition, whether the target domain faults are the same as the source domain faults also affects the choice of transfer learning method in fault diagnosis. If the faults of two domains are identical, the main challenge of transfer learning is to learn the domain-invariant features, and the pre-trained classifier in source domain can be directly used to predict the target faults; if the faults of two domains are not identical, the transfer learning model needs to identify both the common faults of two domains and the source-private or target-private faults to prevent potential negative transfer. Therefore, the fault consistency in the source and target domains is also a key factor in transfer learning model establishment.

III. OPEN-SOURCE BEARING FAULT DATASETS

Intelligent fault diagnosis methods require massive labeled training data. Although it is difficult to obtain sufficient fault data to train the diagnostic model in real industrial machines [89, 90], the labeled fault data in laboratory machines are easy

TABLE I
SUMMARY OF OPEN BEARING FAULT DATASETS.

Categories	Dataset	Signal type	Number of working conditions	Faulty states
Seeded fault dataset	CWRU	Vibration	4	Normal, outer race fault, inner race fault, ball fault
	MFPT	Vibration	9	Normal, outer race fault, inner race fault
	UofO	Vibration	4	Normal, outer race fault, inner race fault
	PU	Current, vibration	4	Outer race fault, inner race fault
Run-to-failure dataset	IEEE PHM 2012	Vibration, temperature	3	-
	XJTU-SY	Vibration	3	Outer race fault, inner race fault, cage fault, mixed faults
	IMS	Vibration	1	Outer race fault, inner race fault, ball fault
	PU	Vibration	4	Outer race fault, inner race fault, mixed faults

to collect and can be used to resolve fault diagnosis tasks in industrial machines. The laboratory data are collected in a controlled environment with pre-set mechanical structure and variable working conditions, and faults are introduced in two ways: artificial bearing damages and accelerated degradation experiments. Artificial bearing damages are based on the work experience of engineers and researchers, so the seeded faults may occur in practical industrial scenarios. The accelerated degradation experiments are efficient ways to acquire degradation data similar to industrial scenarios, which reveal the complete degradation process of bearings from healthy to failure. What is more, the bearing faults in accelerated degradation experiments occur in the same way as the faults in industrial environments. Therefore, the inheritable fault features in the public datasets collected from laboratory machines are feasible to be reused to diagnose bearing fault diagnosis problems of other machines.

A. Dataset Summary

In this part, seven widely used open-source bearing fault datasets are introduced, including: Case Western Reserve University (CWRU) dataset [91], Society for Machinery Failure Prevention Technology (MFPT) dataset [92], University of Ottawa (UofO) dataset [93], Paderborn University (PU) dataset [94], IEEE PHM 2012 Data Challenge dataset [95], Xi'an Jiaotong University and Changxing Sumyoung Technology (XJTU-SY) dataset [96], and Center for Intelligent Maintenance Systems (IMS) dataset [97]. The seven datasets cover vibration, current and temperature signals:

1) Vibration signals are the most widely used signals for bearing fault diagnosis. Sensors, such as accelerometers, are placed on bearing casing to monitor abnormal vibration patterns caused by bearing faults. The abnormal impulse response generated every time the rolling elements pass over the surface of bearing faults can be monitored by sensors for fault diagnosis.

2) Motor current signal gains great attention on bearing fault diagnosis in recent years. Bearing faults influence vibrations that appear at characteristic frequencies in the motor current, analyzing the current patterns can predict fault types [94]. In addition, the advantages of motor current monitoring technique are not requiring additional sensors to measure but can be collected via existing device (such as current transducers).

3) The temperature signals can also be applied in bearing fault diagnosis, as the temperature of bearing elements tends

to increase when working in an abnormal condition. Thermal sensors are placed inside holes close to the bearing external ring to monitor temperature changes and detect faults [95].

According to the occurrence of faults, the above datasets are categorized into two groups: seeded fault dataset and run-to-failure dataset. The detailed information of the seven datasets is shown in Table I.

B. Seeded Fault Dataset

The seeded fault bearing dataset is usually generated by applying artificial damages to bearings for condition monitoring [94]. As one of the most popular seeded fault datasets, the CWRU dataset contains vibration signals collected from accelerometers under different motor loads, with faults seeded on the outer race, inner race, and ball of bearings by electrical discharge machining with different fault diameters. The MFPT and UofO datasets are also vibration signal-based datasets that provide normal, outer race, and inner race fault data under different loads. The PU dataset contains two subsets: seeded fault dataset and run-to-failure fault dataset, where the seeded faults are caused by electrical discharge machining, drilling, and manual electric engraving, and the run-to-failure faults are collected from the outer and inner races of bearings under different rotational speeds, loads, and radial forces. The seeded fault data in PU dataset consist of both current signals collected by current transducers installed between motor and frequency inverter, and vibration signals measured for reference purpose.

C. Run-to-failure Dataset

The run-to-failure dataset is generated from the accelerated degradation experiments of bearings under various working conditions, reflecting the complete life cycle of bearing from new to complete failure. Different fault locations such as outer race, inner race, ball and cage can be obtained at the end of accelerated degradation experiments. The IEEE PHM 2012 dataset is a typical run-to-failure dataset containing two types of signals: vibration and temperature, with two accelerometers and one temperature sensor for data monitoring under different working conditions. For the other three run-to-failure datasets (XJTU-SY, PU, and IMS datasets), only vibration signals are avaiable: the fault data in XJTU-SY and PU datasets are collected from multiple working conditions, and the fault data in the IMS dataset are collected from single working condition.

IV. Deep Transfer Learning in Bearing Fault Diagnosis

Deep transfer learning has gained wide attention and has been successfully applied in the field of bearing fault diagnosis since 2016. In this section, the literature focusing on resolving cross-domain bearing fault diagnosis problem is systematic reviewed. To give readers a comprehensive overview, the mentioned references are summarized in Table II.

A. Inductive Transfer Learning

Inductive transfer learning can be divided into two cases: supervised transfer learning and semi-supervised transfer learning. Supervised transfer learning requires all the target domain labels to be available. Semi-supervised transfer learning allows a large amount of target domain data to be unlabeled with few target domain data labeled during training. Furthermore, supervised and semi-supervised transfer learning are categorized into transfer between different machines and transfer between same machines in this survey according to the fault data origin, as shown in Table III.

1) Supervised Transfer Learning: Supervised transfer learning requires labels to be available in both the source and target domain. Common fault diagnosis tasks based on supervised transfer learning can be divided into transfer between different and same machines (see Table III).

a. Transfer between different machines

In this transfer scenario, the fault data in the target domain are collected from different machines from source domain. Since the mechanical structures, bearing types, working conditions etc. vary in different machines, the distributions of fault data are different. The fault diagnosis model trained using the source domain data can not achieve satisfactory performance without any knowledge transfer. Fine-tune-based methods are widely used when the target domain data are available. The basic idea of fine-tune-based methods are to leverage the diagnostic model from source domain and transfer the model and/or parameters learned to new scenarios in target domain to deal with fault diagnosis problems. Instead of training from scratch, a relatively small learning rate is usually adopted in the re-training of the diagnostic model for the target task. In bearing fault diagnosis, the open-source datasets such as CWRU were utilized by researchers to pre-train deep learning models, which were further fine-tuned by available data collected from real industrial scenarios for target task [98, 99]. In addition, some researchers also attempted to apply non-machinery datasets, such as ImageNet, to pre-train transfer learning models. The top layer of the pre-trained model was replaced to match the number of target labels, then the bearing fault data were applied to fine-tune the pre-trained model for fault diagnosis [75, 80]. It is worth noting that Zhang et al. [80] used vibration and current signals for bearing fault diagnosis, they did not specially design signal preprocessing methods and transfer learning models. Although the fault data collected by different sensors represent the same or similar fault information, the fault data distribution, physical meaning or feature embedding can be very different due to the difference in signal types. Therefore, taking into account the

difference of signal types when aligning the source and target domain features may avoid misalignment.

The above fine-tune-based methods require a certain amount of labeled target data, but such a requirement in label availability can be quite difficult in practical scenarios. In order to address the limited labeled data problem, He et al. [100] investigated a scenario with only one labeled fault sample available in the target domain and proposed an enhanced deep auto-encoder model to improve the quality of the extracted s. Besides the labeled data issue, the features extracted by the frozen layers during the transfer may be irrelevant to the target task, as the existing fine-tune-based studies freeze the network mainly based on experience instead of quantitative analysis. Therefore, Zheng et al. [83] introduced two factors in fine-tune strategy: mean square error (MSE) and structural similarity (SSIM), to assess the similarity of source and target features in each layer. If MSE is low and SSIM is high, then the source and target domain data share common features in the current layer and the layer parameters can be frozen for transfer.

b. Transfer between same machines

In this transfer scenario, the source and target domain data are collected from the same machine but under different working conditions. The existing deep transfer learning-based fault diagnosis methods in literature can be divided into two categories: fine-tune-based and few-shot-based methods.

• Fine-tune-based

In the scenario of transfer between same machines, the features extracted from previous working conditions are quite different from those extracted from new working conditions, causing the problem of feature shift in cross working conditions. In addition, the data are also limited in new working environments. To deal with the feature shift and limited data problems, the fine-tune-based methods are adopted by researchers to improve the performance of diagnostic models in new working environments by transferring the model and/or parameters learned from other working conditions (see Fig. 4(1)). Hasan et al. [101] applied S-transform to convert the time domain data into the time-frequency domain to get better transfer performance, and used CNN-based transfer learning method to diagnose bearing faults. Zhao et al. [102] proposed a novel multiscale neural network to improve the performance of transfer learning by constructing three modules with different dilated convolution kernels to learn domain-invariant features. In the transfer learning stage, the pre-trained multiscale modules were frozen to extract target domain features, and the other parts were fine-tuned based on the limited labeled data. To decide the number of layers for fine-tuning with limited data, Han et al. [103] proposed three fine-tune strategies and suggested the optimal results can be achieved by fine-tuning specific layers and freezing the others. Zhao et al. [104] introduced an ensemble adaptive CNN to realize accurate fault diagnosis and good generalization, by applying pre-trained parameters to initialize the whole network.

Besides the normal factors in working conditions such as rotating speed and working load, the number of sensors is also an important factor in bearing fault diagnosis. Most existing

TABLE II
SUMMARY OF LITERATURE ON DEEP TRANSFER LEARNING-BASED BEARING FAULT DIAGNOSIS.

Reference	Public dataset(s)	Source data	Target data	Transfer between different or same machines	Transfer between different or same faults	Transfer strategy
[27]	/	Labeled	Unlabeled	Same	Different	Statistic-based
[50]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[51]	CWRU, IMS	Labeled	Unlabeled	Same	Same	Hybrid
[63]	CWRU	Labeled	Unlabeled	Same	Different	Adversarial-based
[69]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[70]	CWRU	Labeled	Unlabeled	Different	Same	Statistic-based
[71]	PU	Labeled	Unlabeled	Same	Same	Adversarial-based
[72]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[73]	CWRU	Labeled	Unlabeled	Same	Same	Hybrid
[75]	CWRU	Labeled	Labeled	Different	Same	Fine-tune-based
[83]	IMS	Labeled	Labeled	Different	Same	Fine-tune-based
[84]	CWRU	Labeled	Labeled	Same	Same	Fine-tune-based
[86]	CWRU, PU, XJTU-SY	Labeled	Unlabeled	Different	Different	Adversarial-based
[88]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[89]	CWRU	Labeled	Unlabeled	Different	Same	Statistic-based
[98]	CWRU	Labeled	Labeled	Different	Same	Fine-tune-based
[99]	CWRU, IMS	Labeled	Labeled	Different	Same	Fine-tune-based
[100]	CWRU, IMS	Labeled	Labeled	Different	Same	Fine-tune-based
[101]	CWRU	Labeled	Labeled	Same	Same	Fine-tune-based
[102]	CWRU	Labeled	Labeled	Same	Same	Fine-tune-based
[103]	IEEE PHM 2009	Labeled	Labeled	Same	Same	Fine-tune-based
[104]	/	Labeled	Labeled	Same	Same	Fine-tune-based
[108]	CWRU	Labeled	Labeled	Same	Different	Fine-tune-based
[109]	CWRU	Labeled	Labeled	Same	Different	Fine-tune-based
[110]	PU	Labeled	Labeled	Same	Same	Few-shot-based
[111]	CWRU	Labeled	Unlabeled	Same	Same	Adversarial-based
[113]	CWRU, IMS	Labeled	Limited labels	Different	Different	Statistic-based
[114]	CWRU	Labeled	Limited labels	Different	Same	Statistic-based
[115]	CWRU, IMS	Labeled	Limited labels	Different	Same	Statistic-based
[117]	CWRU, IMS	Labeled	Limited labels	Different	Same	Adversarial-based
[118]	CWRU, PU	Labeled	Limited labels	Different	Different	Adversarial-based
[119]	CWRU, IMS	Labeled	Limited labels	Different	Different	Adversarial-based
[120]	CWRU, IMS	Labeled	Unlabeled	Different	Same	Statistic-based
[123]	CWRU, IMS, XJTU-SY	Labeled	Unlabeled	Different	Same	Statistic-based
[124]	CWRU, PU	Labeled	Unlabeled	Different	Same	Statistic-based
[125]	CWRU	Labeled	Unlabeled	Different	Same	Statistic-based
[126]	PU	Labeled	Unlabeled	Different	Same	Statistic-based
[127]	CWRU, IMS	Labeled	Unlabeled	Different	Same	Statistic-based
[128]	CWRU	Labeled	Unlabeled	Different	Same	Statistic-based
[129]	CWRU, IMS	Labeled	Unlabeled	Different	Same	Few-shot-based
[130]	CWRU	Labeled	Unlabeled	Different	Same	Hybrid
[131]	CWRU, MFPT	Labeled	Unlabeled	Same	Same	Statistic-based
[132]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[133]	CWRU, PU	Labeled	Unlabeled	Same	Same	Statistic-based
[134]	/	Labeled	Unlabeled	Same	Same	Statistic-based
[135]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[136]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[137]	CWRU, MFPT	Labeled	Unlabeled	Same	Same	Statistic-based
[138]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[140]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[141]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[142]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[143]	/	Labeled	Unlabeled	Same	Same	Statistic-based
[144]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[145]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[146]	CWRU	Labeled	Unlabeled	Same	Same	Statistic-based
[147]	IEEE PHM 2009	Labeled	Unlabeled	Same	Same	Adversarial-based
[148]	CWRU	Labeled	Unlabeled	Same	Same	Adversarial-based
[149]	CWRU	Labeled	Unlabeled	Same	Same	Adversarial-based
[150]	CWRU	Labeled	Unlabeled	Same	Same	Adversarial-based
[151]	/	Labeled	Unlabeled	Same	Same	Adversarial-based
[152]	/	Labeled	Unlabeled	Same	Same	Adversarial-based
[153]	CWRU	Labeled	Unlabeled	Same	Same	Adversarial-based
[154]	CWRU, PU	Labeled	Unlabeled	Same	Same	Hybrid
[155]	CWRU	Labeled	Unlabeled	Same	Same	Hybrid
[156]	CWRU	Labeled	Unlabeled	Same	Same	Adversarial-based
[157]	CWRU	Labeled	Unlabeled	Same	Same	Adversarial-based
[158]	PU	Labeled	Unlabeled	Same	Same	Adversarial-based
[159]	CWRU	Labeled	Unlabeled	Same	Same	Few-shot-based
[161]	/	Labeled	Unlabeled	Same	Same	Hybrid
[162]	CWRU	Labeled	Unlabeled	Same	Different	Adversarial-based
[163]	CWRU	Labeled	Unlabeled	Same	Different	Adversarial-based
[164]	CWRU	Labeled	Unlabeled	Same	Different	Adversarial-based

* / represents no public dataset mentioned in Section III is used in the reference, limited labels represent few target domain data labeled and the remaining are unlabeled, none represent target domain data are not available.

TABLE III
SUMMARY OF INDUCTIVE TRANSFER LEARNING IN BEARING FAULT DIAGNOSIS.

| Inductive transfer learning scenario		Methods	References
Supervised transfer learning	Transfer between difference machines	Fine-tune-based	[75],[80],[83],[98],[99],[100]
	Transfer between same machines	Fine-tune-based	[84],[101],[102],[103],[104],[107],[108],[109]
		Few-shot-based	[110]
Semi-supervised transfer learning	Transfer between difference machines	Statistic-based	[113],[114],[115]
		Adversarial-based	[117],[118],[119]
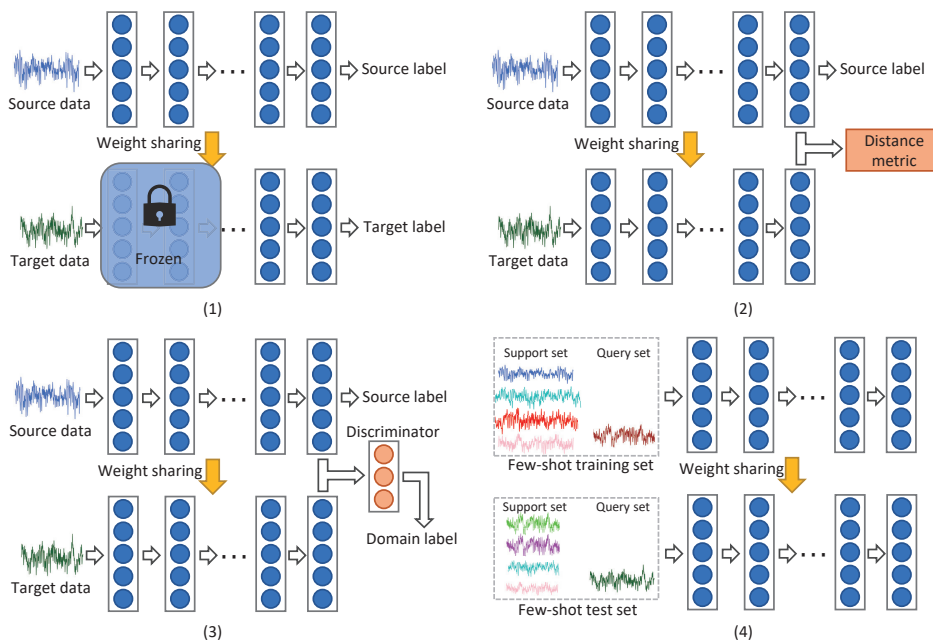
Fig. 4. Basic frameworks of four typical deep transfer learning models: (1) fine-tune-based methods, (2) statistic-based methods, (3) adversarial-based methods, (4) few-shot-based methods.

bearing fault diagnosis methods are mainly based on the measurement of single sensor only, but one sensor may not be able to provide comprehensive information for better fault diagnosis result, as the amplitude and phase of measurement is significantly affected by the sensor location. In addition, one sensor is easily disturbed by external noise and interference, which may lead the collected signals to become unreliable for fault diagnosis and fail to reflect complex fault features. Multi-sensors placed at different positions provide additional information of bearing status to avoid misdiagnosis. However, multi-sensors also bring redundant and irrelevant features, the determination of optimal sensor location is very challenging, especially considering the contributions of sensors at different locations. Di et al. [107] proposed voting strategies to transfer valuable faulty information from several sensors and showed that multisensor signal with voting strategies could achieve accurate diagnosis using only one labeled target data.

In bearing fault diagnosis, it is normal to have different fault labels between target domain and source domain. To resolve such a label inconsistency problem, the fine-tune-based methods were adopted by replacing the output layer of the pre-trained model with a new one of the same dimension as target labels [108, 109]. Besides replacing the output layer, Kim et al. [108] also proposed a selective parameter freezing (SPF)

strategy to freeze output-sensitive parameters while tuning the model. The test results showed that the SPF strategy could acquire better performances compared with other fine-tune strategies, such as freezing, partial freezing, and basic fine-tune.

- Few-shot-based

In some extreme scenarios, only a small amount of fault data are available, restricting the accuracy of the data-driven fault diagnosis model. As a promising machine learning method, few-shot learning can generalize to unseen but related tasks from limited instances. In addition, few-shot learning methods do not require a large amount of labeled data to achieve satisfactory prediction results and reduce data collection and computational cost. Therefore, when encountering fault diagnosis problems with limited data, researchers usually apply few-shot learning methods to address domain shifts between different working conditions or machines. Few-shot-based transfer learning is a kind of representative few-shot learning methods [110], which commonly use limited source domain data to pre-train fault diagnosis models and predict unseen but related faulty labels based on a prior knowledge (see Fig. 4(4)). To deal with such a limited sample problem in practical fault diagnosis scenarios, Wu et al. [110] proposed a meta relation network with a feature encoder and a metric learner:

the feature encoder mapped the input data into a unified feature space, and the metric learner adaptively learned a distance metric function according to extracted features. The test results demonstrated that the proposed meta relation network achieved good performance with extremely few-shot instances.

2) Semi-supervised Transfer Learning: Semi-supervised transfer learning combines the situation where few fault data are labeled with a large amount of unlabeled data in the target domain, which provides an efficient way to utilize both labeled and unlabeled data. Introducing massive auxiliary unlabeled data in the target domain enables transfer learning models to exploit common latent features belonging to the source and target domain data. Existing semi-supervised transfer learning methods can be classified into statistic-based and adversarial-based methods (see Table III).

- Statistic-based

The basic idea of statistic-based transfer learning aims at learning the domain-invariant representation by minimizing the distribution discrepancy of source and target domains (see Fig. 4(2)). Maximum mean discrepancy (MMD) is the most commonly used metric to evaluate the data distribution distance, as shown in (1):

$$\text{MMD}^2(\mathbf{X}^s, \mathbf{X}^t) = \left\| \frac{1}{n}\sum_{i=1}^{n}\phi(\mathbf{x}_i^s) - \frac{1}{m}\sum_{j=1}^{m}\phi(\mathbf{x}_j^t) \right\|_{\mathcal{H}_k}^2 \quad (1)$$

where $\mathbf{X}^s = \{\mathbf{x}_1^s, \cdots \mathbf{x}_n^s\}$ and $\mathbf{X}^t = \{\mathbf{x}_1^t, \cdots, \mathbf{x}_m^t\}$ denote source and target data, ϕ denotes kernel function that maps the source and target data into reproducing kernel Hilbert space (RKHS), and n and m are the number of source and target samples respectively [111, 112].

Tzeng et al. [112] firstly applied MMD in deep domain confusion (DDC) network for transfer learning. By minimizing the classification loss and MMD which measures the distribution discrepancy of two domains simultaneously, DDC network can learn domain-invariant features of the source and target domain data, with the loss function shown in (2):

$$\mathcal{L} = \mathcal{L}_C(\mathbf{X}_L, \mathbf{y}) + \lambda\text{MMD}^2(\mathbf{X}^s, \mathbf{X}^t) \quad (2)$$

where $\mathcal{L}_C(\mathbf{X}_L, \mathbf{y})$ is the classification loss on data $\mathbf{X}_L$ and ground truth label y, $\text{MMD}^2(\mathbf{X}^s, \mathbf{X}^t)$ refers to the distance between the source data $\mathbf{X}^s$ and target data $\mathbf{X}^t$, and λ is a trade-off parameter.

In order to address the problem of transfer between different machines, Li et al. [113] proposed a two-stage knowledge transfer scheme. First, an auto-encoder network with an auxiliary classifier was built to extract common fault features between the source and target domain data in a supervised manner. Second, the pre-trained encoder was used to predict feature distribution and MMD was introduced to measure the feature distribution discrepancy. Discrepancy criterion plays a critical role in statistic-based methods, Zhou et al. [114] proposed that in addition to measure distribution, conditional distribution should also be considered during domain adaptation. The proposed joint statistic metric was tested on nine transfer learning tasks and the experimental results verified their assumptions. To address the problem of few labeled data

in the target domain, Wu et al. [115] proposed to generate auxiliary data from the labeled source domain using a batch-normalized long-short term memory. Next, a transfer maximum classifier discrepancy criterion was designed to align the generated auxiliary data with the unlabeled target domain data.

- Adversarial-based

Adversarial-based methods were inspired by generative adversarial neural network, a promising machine learning algorithm in the form of a zero-sum game (see Fig. 4(3)). To extract domain-invariant features from the source and target domain data, Ganin et al. [116] proposed domain adaptation neural network (DANN), an adversarial-based deep transfer learning method, with three modules: feature extractor, domain discriminator, and classifier. The feature extractor extracts domain-invariant representations from the source and target domain data, and the classifier and domain discriminator predict the class and domain labels respectively [105, 106]. The loss function of DANN is shown as follows:

$$\mathcal{L}(\theta_f, \theta_y, \theta_d) = \sum_{i=1}^{N}\mathcal{L}_y^i(\theta_f, \theta_y) - \lambda\sum_{i=1}^{N}\mathcal{L}_d^i(\theta_f, \theta_d) \quad (3)$$

where $\mathcal{L}_y^i(\cdot)$ and $\mathcal{L}_d^i(\cdot)$ are the losses of classifier and discriminator at the ith training example respectively, θ_f, θ_y, and θ_d denote the parameters of feature extractor, classifier, and discriminator respectively, and λ refers to the trade-off parameter. The goal of domain adversarial-based methods is to seek the parameters $\hat{\theta}_f$, $\hat{\theta}_y$, and $\hat{\theta}_f$ that deliver a saddle point of loss function (3):

$$(\hat{\theta}_f, \hat{\theta}_y) = \arg\min_{\theta_f, \theta_y}\mathcal{L}(\theta_f, \theta_y, \hat{\theta}_d) \quad (4)$$

$$\hat{\theta}_d = \arg\max_{\theta_d}\mathcal{L}(\hat{\theta}_f, \hat{\theta}_y, \theta_d) \quad (5)$$

Based on DANN model, Wang et al. [117] proposed to apply labeled source domain data and limited labeled target domain data to train the feature extractor and classifier in a supervised manner. To learn the domain-invariant features, a discriminator is employed to align latent features. Considering the extremely limited fault data scenario such as single sample, Han et al. [118] proposed multiple domain discriminators to enhance the domain-invariant feature extraction and improve the fault diagnosis performance. Diverse from [118], Li [119] used multiple classifiers to achieve accurate fault prediction leveraging label information. A discriminator was also applied to align the source and target features.

B. Transductive Transfer Learning

In this review, the existing transductive transfer learning methods in bearing fault diagnosis are divided into transfer between different machines and transfer between same machines according to the origin of the target domain data. In addition, the methods under transfer between different/same machines scenarios are further categorized into transfer between same faults and transfer between different faults according to the fault label property.

TABLE IV
SUMMARY OF TRANSDUCTIVE TRANSFER LEARNING BETWEEN
DIFFERENT MACHINES IN BEARING FAULT DIAGNOSIS.

Transductive transfer learning scenario	Methods	References
Transfer between same faults	Statistic-based	[70],[89],[120],[123],[124] [125],[126],[127],[128]
	Few-shot-based	[129]
	Hybrid	[130]
Transfer between different faults	Adversarial-based	[86]

1) Transfer Between Different Machines: The time and frequency domain characteristics of bearing signals are greatly affected by machine types and structures, so the feature distributions of different machines can be very different. In order to resolve the feature difference problem between different machines, researchers have proposed various methods using deep transfer learning techniques, including statistic-based, adversarial-based and few-shot-based methods, as shown in Table IV.

a. Transfer Between Same Faults

- Statistic-based methods

Statistic-based methods have received ample attention in recent years in bearing fault diagnosis. Zhao et al. [70] and Guo et al. [120] applied MMD to measure the distribution discrepancies of the source and target bearing datasets. Nevertheless, the authors did not consider the impact of internal covariate shift and only aligned the data distribution of the source and target domain data in the fully connected layer [121]. Therefore, Yang et al. [89] proposed a multilayer domain adaptation bearing fault diagnosis model by applying MMD in each layer to minimize the distribution discrepancy of the source and target domain data. The goal of the above methods is to reduce the marginal distributions between the source and target domain data, based on the assumption that the conditional distributions between the two domains are the same. However, previous study claimed that minimizing both marginal and conditional distributions is vital to constructing a robust transfer learning model [122–124]. Based on this viewpoint, Wu et al. [125] applied joint distribution adaptation to match marginal and conditional distributions by MMD for bearing fault diagnosis, and the test results on CWRU and IMS datasets demonstrated that minimizing joint distribution can achieve effective fault diagnosis with few fault data. However, for fault diagnosis problem, healthy state data account for a large proportion of the collected data samples as equipment is healthy most of the time. Previous methods ignore the class difference and assume that the number of training samples for each class is equal. Cao et al. [126] found that neglecting the class weight difference can cause performance decline in MMD-based methods, thus, they added a class probability penalty term to MMD to address the category imbalance problem. Li [127] et al. claimed that single source to single target transfer learning tasks can not provide comprehensive fault features for target fault diagnosis tasks. Therefore, they proposed a reinforcement ensemble deep transfer learning method with various kernel MMD to learn fault features

from different sources. Most deep transfer learning-based fault diagnosis methods aim to learn domain invariant features of two domains and neglect the generalization of models on the target domain, therefore, Zhang et al. [128] proposed to use an MMD loss to minimize global domain distribution discrepancy and a supervised contrastive learning loss to realize class-level alignment.

- Few-shot-based methods

As discussed before, few-shot learning can predict fault labels based on limited samples. To conduct bearing fault diagnosis with small data, Lu et al. [129] constructed a transfer relation network with FeatureNet and RelationNet: the FeatureNet learns fault feature representations from the sample and query sets, and the RelationNet computes the relation score of feature vectors. According to the proposed transfer relation network, a query vector from the unlabeled target domain is classified into the category with the highest relation score. The experimental results on three public datasets demonstrated that the proposed method could efficiently predict faulty labels in the case of small data.

- Hybrid methods

Global domain adaptation is widely used in cross-domain bearing fault diagnosis, and the pre-trained source classifier can theoretically predict target faults. However, only aligning the global data distribution while ignoring the distribution differences between each class may lead samples near the classification boundary to be misclassified to other classes. Therefore, Liu et al. [130] proposed a global domain and subdomain jointly adaptation method for cross-domain bearing fault diagnosis problems. An adversarial-based network was proposed to extract global domain invariant features from input data, and a local MMD module was applied to minimize subdomain distribution discrepancy. Experiments were carried out on the CWRU dataset and a self-designed platform, and the experimental results showed that the proposed global domain and subdomain jointly adaptation method achieved better performance compared with global domain adaptation methods.

b. Transfer Between Different Faults

The great success of cross-machine bearing fault diagnosis is mainly based on the assumption that the target label space is the same as the source label space. However, the target fault information is unseen in most practical industrial scenarios, which brings a new challenge for knowledge transfer between different machines and different faults. To address the inconsistent label and insufficient data problems, Deng et al. [86] introduced a double layer attention-based discriminator for bearing fault diagnosis. The proposed attention mechanism enabled the model to determine which discriminator should be concentrated and which part of the source domain feature should be shared with the target domain and avoid negative transfer.

2) Transfer Between Same Machines: Transfer between same machines under different working conditions is the most common transfer learning scenario. The existing studies can be categorized into two branches: transfer between same faults and transfer between different faults. Transfer between same

TABLE V
SUMMARY OF TRANSDUCTIVE TRANSFER LEARNING BETWEEN SAME MACHINES IN BEARING FAULT DIAGNOSIS.

Transductive transfer learning scenario	Methods	References
Transfer between same faults	Statistic-based	[47],[50],[69],[72],[88],[131], [132],[133],[134],[135],[136], [137],[138],[140],[141],[142], [143],[144],[145],[146]
	Adversarial-based	[71],[111],[147],[148],[149], [150],[151],[152],[153],[156], [157],[158]
	Few-shot-based	[159],[160]
	Hybrid	[51],[73],[154],[155],[161]
Transfer between different faults	Statistic-based	[27]
	Adversarial-based	[63],[162],[163],[164]

faults contains statistic-based, adversarial-based, and hybrid methods, and transfer between different faults only contains adversarial-based methods, as shown in Table V.

a. Transfer Between Same Faults

- Statistic-based methods

As mentioned in previous paragraphs, MMD and its variants are widely used in statistic-based transfer learning methods [50, 69, 111, 126, 131, 132]. In addition to MMD and its variants, many other metrics are also used to compute the distribution discrepancy, including: moment discrepancy [133, 134], high order Kullback–Leibler divergence [135], correlation alignment (CORAL) [72], maximum variance discrepancy [136], Wasserstein distance [137], etc. Due to the limited representation ability of single kernel MMD [139], some researchers applied multiple kernel MMD to balance multiple kernel functions in measuring the distribution discrepancy between two datasets [84, 131, 140], as shown in (6):

$$\mathcal{K} := \left\{ k : k = \sum_{u=1}^{m} \beta_u k_u, \sum_{u=1}^{m} \beta_u = 1, \beta_u \geq 0, \forall u \right\} \quad (6)$$

where β_u is the trade-off parameter and k_u is a positive kernel function.

Most existing statistic-based methods focused on aligning marginal distributions, that is, minimizing the distribution discrepancy of the whole domain. By considering conditional distributions, Wang et al. [88] developed a conditional distribution-based adaptive network with MMD to minimize the intra-class distribution discrepancy between the source and target domain data. Furthermore, by considering both contributions of domain alignment and categories alignment, some researchers proposed a joint distribution adaptation (JDA) method to align both marginal and conditional distributions in bearing fault diagnosis [137, 138, 141, 142], and achieved better performance than aligning marginal distribution only based on experimental results. In addition, Pang et al. [143] and Kang et al. [144] proposed to minimize the distribution divergence and geometrical distance together to align the two domain features. The experimental results showed that jointly reducing distribution divergence and geometrical distance can effectively increase transfer learning performance compared with methods that consider only distribution divergence. Tian

et al. [145] proposed that multiple source domain data collected from different working conditions can provide comprehensive fault information compared with a single source domain, therefore a multi-branch neural network was built to fuse each source domain features. Experimental results verified the effectiveness of the proposed multi-source transfer learning method for cross-domain bearing fault diagnosis problems.

- Adversarial-based methods

Adversarial-based transfer learning methods have been widely applied in cross working condition transfer tasks. To tackle the challenge of limited labeled data, researchers applied deep adversarial convolutional neural network to learn domain-invariant features for bearing fault diagnosis [146–148]. In order to improve the transfer capability, researchers proposed both multidiscriminator adversarial network and multilayer adversarial network to learn domain-invariant features and recognize feature discrepancy between the source and target domain data [149, 150]. It is worth noting that the above methods only focus on aligning the global characteristics of source and target domain data, but neglect the category information of different faults. To deal with the above problem, Jiao et al. [151] proposed a double-level adversarial transfer learning model to promote both domain-level and class-level distribution alignments in bearing fault diagnosis. In order to address the equilibrium issue of adversarial-based methods, Xia et al. [152] proposed a perceptual loss to align the source and target domain distribution to increase the stability of training. In addition, most deep transfer learning bearing fault diagnosis methods focus on single-task-domain and neglect the scenario where multi-target-domain in practical applications. The complex data distribution structure of multi-target may cause samples close to the decision boundary to be misclassified. To bridge this gap, Deng et al. [153] proposed a multi-target-domain adaptation method with a correlation regularization mechanism to suppress negative transfer of ambiguous samples.

- Few-shot-based methods

Few-shot-based transfer learning methods have made excellent progress in limited faulty data problems. Zhang et al. [159] applied a Siamese neural network-based few-shot learning method to deal with cross-working condition fault diagnosis problems, and the performance of the proposed method was verified by CWRU dataset in cross-working conditions.

When there is no data available in the target domain, the few-shot problem degenerates into the zero-shot problem. As a special case of few-shot learning, zero-shot learning can predict samples that are not observed during training without any target data or identical distribution requirements. To recognize faults in unknown working conditions, Gao et al. [160] proposed a contractive stacked autoencoder based zero-shot learning method, and the experimental results showed that the proposed method can achieve better performance than conventional fault diagnosis methods.

- Hybrid methods

In order to further improve fault diagnosis performance, some researchers proposed hybrid methods by combining several transfer learning approaches. For example, adding the

statistic distribution discrepancy onto the loss function of adversarial-based transfer learning methods as a penalty term to minimize domain distribution shift. Shao et al. [73] and Wan et al. [51] integrated MMD and adversarial domain adaptation strategy to extract domain-invariant features of two domains. Wu et al. [155] proposed to use domain adversarial training with an intra-class MMD loss to minimize the marginal and conditional distribution of the source and target domain. Considering the effect of noise in transfer learning, Qian et al. [161] used convolutional autoencoder as the feature extractor by integrating class, domain, and CORAL losses in the adversarial-based transfer learning model, to reduce the impact of noise and minimize the distribution discrepancy between the source and target domain data. Numerous deep transfer learning fault diagnosis methods can not perform well when lacking of enough labeled data, Fan et al. [154] proposed a weighted quantile discrepancy metric to access the influence of different quantiles on domain transfer and integrated it into adversarial-based methods to realize accurate fault prediction.

b. Transfer Between Different Faults

• Statistic-based methods

Most transfer learning methods for bearing fault diagnosis assumed that the source and target domains have identical label space. Nevertheless, it is normal to have different fault labels between target domain and source domain in practical scenarios. For example, the bearing faults in the source domain may not cover all the faults in the target domain, leading to the source domain data can not provide comprehensive fault information for target fault diagnosis tasks. To address this problem, Yang et al. [27] proposed a multi-source domain transfer strategy to take advantage of multiple source domain fault information. Specifically, a partial distribution adaptation sub-network with an unseen fault identify neuron was proposed to avoid misalignment. Next, multiple partial distribution adaptation sub-networks were weighted fused to release the effects of the source and target domain label spaces inconsistent.

• Adversarial-based methods

Another scenario where the source and target domain label spaces are inconsistent is that the target domain only contains part of the source domain faults. Li et al. [63] proposed a class-weighted adversarial network to address the partial transfer learning problem in bearing fault diagnosis, by assigning different weights to the source domain classes according to the discriminator output to indicate the similarities between the source and target domain data. Then the source domain classes with low weights were neglected, and only partial source domain knowledge was transferred to the target domain for fault diagnosis.

In practical fault diagnosis scenarios, the target domain data may contain some unknown classes that do not exist in the source domain or only a source domain dataset is accessible, bringing challenges for domain adaptation. In order to address unknown fault problem in the target domain, Li et al. [162] proposed a stacked autoencoder transfer learning method for fault diagnosis, with a trained encoder to extract latent common features between the source and target domain

data, and a binary classifier to recognize new faulty label in the target domain. Zhang et al. [163] introduced an outlier classifier on original domain adversarial neural network [116] to recognize unknown faults in the target domain. Based on previous work, Zhang et al. [164] further investigated universal domain adaptation problems by proposing class-level alignment mechanisms to recognize the target unknown faults while aligning the shared faulty features. The proposed method can not only correctly classify the target instances that are included in the source domain but also mark the outliers as unknown.

V. QUALITATIVE ANALYSIS

Many works showed that deep transfer learning-based bearing fault diagnosis is effective and can achieve higher accuracy than training from scratch when the target domain data are limited, or the distributions of the source and target domain data are different. Inspired by [165], the author introduced six criteria to assess their characteristics in Table VI: 1) label dependency: if the method requires the target labels; 2) data scalability: if the method requires large datasets to train the model; 3) deployment difficulty: if the method is difficult to deploy; 4) efficiency: the computational cost of the method; 5) extensibility: if the method can be modularized and expanded by replacing the existing modules or adding new modules to resolve more complex problems or achieve better performance; 6) performance: diagnostic accuracy of the method.

1) Fine-tune-based methods: Fine-tune-based methods can be theoretically used to solve most transfer learning problems in bearing fault diagnosis if the following two assumptions are satisfied: sufficient target domain data, and all target labels are available. On one hand, as fine-tune-based methods have a strong dependence on the target domain labels because the pre-trained model needs to tune the parameters in a supervised manner. Correspondingly, the model can also realize high diagnostic accuracy on the target diagnosis tasks with the guidance of the target label. On the other hand, the quantity of available data can significantly influence model performance. When the data distribution discrepancy between two domains is large, insufficient target domain data may leave the model stuck in a local minimum and can not generalize well. In addition, fine-tune-based methods freeze partial parameters during tuning, which do not require as much training data as statistic-based and adversarial-based methods. Therefore, the data scalability and computational efficiency are medium compared with the other three methods. Due to the diagnosis model being pre-trained on the source domain data and the target domain labels being available, the pre-trained model can be re-used to learn target fault features in supervised learning, so fine-tune-based methods are easy to deploy on various fault diagnosis tasks. In terms of extensibility, fine-tune-based methods can be easily used to resolve the label-set inconsistency problem between the source and target domains by replacing the top layer according to the target tasks.

2) Statistic-based methods: Statistic-based methods usually introduce a metric to measure the feature distribution discrepancy between the source and target domains in the embedding

TABLE VI
COMPARISON OF DIFFERENT TRANSFER LEARNING METHODS (*: LOW, **: MEDIUM, ***: HIGH).

Methods	Label dependency	Data scalability	Deployment difficulty	Efficiency	Extensibility	Performance
Fine-tune-based	***	**	*	**	**	***
Statistic-based	*	***	**	*	*	***
Adversarial-based	*	***	***	*	***	***
Few-shot-based	*	*	**	***	*	**

space. When the feature distribution discrepancy is less than a certain threshold, the features of the source and target domains are considered to be similar. Therefore, the classifiers trained on the source domain data can be shared with the target fault diagnosis tasks, without any label requirement on the target domain data. In addition, most of the statistic-based methods only need a metric to measure the distribution discrepancy of two domains and do not need any additional modules in the pre-trained model or change in the structure of the pre-trained model, which means the statistic-based methods are not as difficult to deploy as adversarial-based methods. To achieve high diagnosis accuracy on the target domain data, enough unlabeled target data are necessary for feature extraction and fault classification. Therefore, statistic-based methods have a high demand on data scalability, and accordingly, the cost on computational resources also increases. In terms of extensibility, it is difficult for most statistic-based methods to resolve complex fault diagnosis problems, such as label-set inconsistency problem, due to the limited hyperparameters in the statistic-based methods and the pre-trained classifier can not perform well on unseen target faults. Although the method structures are not complicated, these methods can still realize satisfying performance if the metric and structure are well-designed [165, 166].

3) Adversarial-based methods: The success of generative adversarial network has motivated many researchers to apply adversarial strategy to resolve domain shift problems, such as intelligent fault diagnosis. Adversarial-based methods aim to generate source and target common features in the form of a zero-sum game by introducing an additional discriminator to distinguish extracted features, the common feature extractor tries to generate domain-invariant features to fool the discriminator. Although adversarial-based methods do not need the target labels, they have high dependencies on data scale and computational resources. On one hand, the introduction of an additional domain discriminator module increases the amount of parameters, which also increases computational cost; on the other hand, the performance of adversarial-based methods relies on the convergence of a zero-sum game between the feature extractor and discriminator, which is difficult to optimize on small datasets [165]. Furthermore, the additional discriminator and the gradient reversal layer make the adversarial-based methods difficult to deploy compared with the other three methods, but the complexity leaves more room for improvement to improve diagnosis accuracy or address complex fault diagnosis tasks, such as label inconsistent problems [86, 118, 163, 164]. In terms of performance, adversarial-based methods always have high prediction results in various machines and working conditions with sufficient

training data [104].

4) Few-shot-based methods: Few-shot-based methods provide a new paradigm, different from the above mentioned methods, by learning knowledge of how-to-learn to resolve the given fault diagnosis tasks. Few-shot learning can address uncommon fault diagnosis cases that conventional deep learning models cannot solve, such as zero or limited faulty data, getting rid of the cumbersome and expensive data collection and labeling process. Therefore, few-shot-based methods have low dependency on data label and data scalability, expensive fault data collection and labeling works are eliminated. Furthermore, less data quantity means training the fault diagnosis model does not require large amount of computational resource. Notably, although few-shot-based methods do not require large amount of training data, they need to construct various training tasks and test tasks to build a generalized model (see Fig. 4(4)). The deployment of few-shot-based methods is not as easy as fine-tune-based methods that inherit pre-trained models, but not as difficult as adversarial-based methods that require additional modules. Limited by the size of training data, the general performance of few-shot-based methods cannot compete with the three methods mentioned above.

VI. CHALLENGES AND OPPORTUNITIES

Deep transfer learning has received much attention in bearing fault diagnosis since 2016. The introduction of deep transfer learning methods alleviates the challenge of insufficient data in the target domain to a certain extent by reusing the knowledge learned from the source domain. Nevertheless, there are still some unsolved problems in deep transfer learning-based bearing fault diagnosis. In order to further improve the accuracy of diagnostic models in cross-domain tasks and promote the implementation of deep transfer learning, the possible challenges and opportunities are discussed in this section.

A. Transferability Assessment

Deep transfer learning aims to leverage the transferable features learned from different but related tasks to address problems such as limited sample. Unfortunately, the effectiveness of deep transfer learning highly relies on the following two assumptions: 1) the data distributions in the source and target domains are similar; 2) the learning tasks of both domains are similar. If a priori knowledge is transferred from an unrelated field, the performance of transfer learning can be greatly affected, as not all the knowledge extracted from the source domain effectively improves the performance of the target task [167, 168]. Therefore, the assessment of knowledge or

data transferability is critical for building accurate and robust deep transfer learning models. The transferability assessment can avoid negative transfer and provide proper guidance for choosing appropriate diagnostic knowledge from the source domain for target tasks [169, 170]. To the best of the authors' knowledge, there is no comprehensive study discussing the knowledge transferability of source domain data in bearing fault diagnosis. Therefore, transferability assessment should be given much attention in the future work of deep transfer learning-based bearing fault diagnosis. Designing an effective matrix to evaluate the transferability of the source domain samples, features or pre-trained models rather than aligning the whole datasets would effectively improve the transfer model performance and computational efficiency. For example, introducing weights on feature-level or model-level to assess whether the source domain features and/or model parameters can be transferred to resolve the target tasks.

B. Transfer With Distinct Labels

In most scenarios, the fault types of the target domain are unknown, and the fault data may be inaccessible or unavailable too. When the fault labels in the target domain are different from those in the source domain, such a label inconsistency problem increases the difficulty of knowledge transfer, especially when the diagnostic knowledge needs to be transferred from the artificial faults to the real faults. Therefore, the inconsistency between the source and target label spaces is a very challenging problem in deep transfer learning-based bearing fault diagnosis. The challenge of transfer with distinct labels requires accurate recognition of valuable features in the source domain and proper classification of new faults in the target domain. It is worth noting that when target labels are different from source labels, understanding the feature alignment mechanism of each category can potentially contribute to an accurate fault diagnosis model. From literature review, although some research has been carried out on the problem of distinct labels between the source and target domains [86, 98, 118, 119], far too little attention has been paid to unseen faults during transfer learning. For example, most of the authors regarded the target implicit samples as "unknown" class without identifying what faults they were. Therefore, transfer with distinct labels is still a challenging problem in fault diagnosis, which requires new breakthroughs not only in the performance of known classes but also in identifying unknown classes.

C. Transfer Under Abnormal Data Quality

Bearings usually run in harsh environments with heavy loads and high speeds, it is inevitable that the collected bearing status signals contain a large amount of background noise generated by the friction and collision among mechanical elements. Especially for incipient faults, fault signals with small magnitudes are submerged in background noise, the fault features are too weak to be extracted by diagnosis models for fault diagnosis. When the data is extremely noisy with outliers, such as the vibration signal in practical mechanical system, deep learning models may not be able to effectively extract

fault features, and will eventually affect the performance of fault diagnosis. Such an abnormal data quality problem is very common in bearing fault diagnosis, and is highly related to the signal-to-noise ratio and signal segmentation in data collection and preprocessing [171–176]. Current works usually employ signal filtering algorithms or robust models to increase fault diagnosis accuracy, but rarely apply transfer learning to address noise problems in bearing fault diagnosis. Generally, it is convenient and feasible to obtain enormous source domain data from equipment in the laboratory. Therefore, the domain invariant features extracted from the source domain in the laboratory can provide additional knowledge for the target tasks with abnormal data quality. As a result, it is important to investigate further on the deep transfer learning methods to reduce the impact of abnormal data quality and transfer knowledge from laboratory equipment to practical system.

D. Transfer between different signal types

In recent years, sensor technology has developed rapidly, and different types of sensors are widely used in bearing fault monitoring [7]. But for deep transfer learning-based bearing fault diagnosis, most researchers focus on transfer between different working conditions, machines or faults using the same signal types but neglect the scenario where transfer between different signal types. In some scenarios, the source domain signal types are different from the target domain signal types. For example, if the source domain data are vibration signals, but only current or temperature signals are available in the target domain. Although the fault data collected by different sensors represent the same or similar fault information, due to the difference of signal types, the fault data distribution, physical meaning and feature embedding are different. Therefore, the pre-trained diagnosis model using different signal types can not be directly used to predict bearing faults. Applying transfer learning methods to reduce signal distribution discrepancy can address distribution shift problems and reduce computational costs rather than training from scratch. It is worth noting that directly aligning the fault signals collected from different sensor types may cause negative transfer since representations of different signal types are inconsistent. A potential method to avoid misalignment is to project different signal types into a common feature space, followed by feature alignment.

E. Multi-source Transfer

Most existing deep transfer learning-based fault diagnosis methods only used a single source dataset in the learning stage, but such a single-modal transfer may be deficient when significant data distribution divergence exists between source and target domains. In addition, a single source dataset is easily effected by external noise and interference, which may lead diagnosis models to fail to extract complete features from fault data. Therefore, the multi-source transfer learning strategy should be considered as a promising research direction for bearing fault diagnosis. The general multi-source transfer strategies in bearing fault diagnosis include multiple sensor locations, multiple sensor types (vibration sensors, temperature

sensors, current transducers, etc.), or both. First of all, multiple data sources provide more comprehensive data characteristics for the feature extractor compared with single data source. Secondly, multiple data sources can help increase the data diversity and reduce the risk of overfitting during the pre-training process [177, 178]. In addition, large volumes of source data can take advantage of deep neural networks and enable the feature extractor to learn valuable features from the source domain. Thirdly, if some modalities are missing or un-available, the remaining modalities can still provide sufficient inheritable knowledge. Lastly, multiple modalities increase signals' diversity. Each modal provides unique fault features that cannot be obtained from other modalities. However, it is worth noting that although multi-source transfer may provide more information than a single source, it may also bring redundant features that can eventually weaken the performance of transfer learning models. In addition, different modalities have varied contributions for different target fault diagnosis tasks, and unnecessary source domain data may cause negative transfer. Therefore, the impact of redundant features on the target task should not be neglected, and it is important to strike a balance between data diversity and redundancy during the investigation of multi-source transfer learning in the future. A straightforward way is to design efficient feature fusion technologies to fuse common knowledge in feature-level [179]. The authors believe that choosing limited and appropriate data sources is an effective and feasible approach to avoid data redundancy instead of blindly increasing the number of data sources.

F. Incipient Fault Diagnosis

According to the literature review, existing deep transfer learning-based fault diagnosis methods mainly focus on the permanent or serious faults, but the incipient faults are rarely considered. However, it is already known that many severe faults in rolling bearing actually evolve from incipient faults with small magnitudes first, therefore the incipient fault di-agnosis is of great importance for efficient component main-tenance or replacement. However, the incipient fault, due to its small magnitude, is easily interfered by intense background noise which increases the difficulty of incipient fault diagnosis [180–182]. The slight difference between normal features and incipient fault features also brings challenge to extract knowl-edge reflecting incipient faults, making the incipient fault diagnosis of rolling bearing extremely challenging [42]. As a result, the conventional machine learning-based fault diagnosis methods may not be sensitive to incipient faults. With the help of extracted incipient fault features from the source domain data (such as laboratory), the diagnostic knowledge sensitive to incipient faults can be transferred to the target domain to deal with incipient fault diagnosis tasks. Therefore, the investigation on applying deep transfer learning techniques on the incipient fault diagnosis is a promising research direction in the fault diagnosis of rolling bearings.

G. Novel Applications in Transfer Between Different Ma-chines

Transfer between same machines but different working conditions has received wide attention since 2016, and has achieved good performances due to the close relationship between two domains [59, 70]. Affected by various factors such as machines, sensors, and data collection, transfer be-tween different machines is of greater practical importance and more difficult than transfer between same machines in applications. Nevertheless, the existing studies in transfer between different machines are much fewer than the studies in transfer between same machines in the literature. Due to the significant differences in mechanical structures, working environments, and bearing types of different machines, the diagnostic knowledge learned from the source domain (such as laboratory) is always challenging to be reused in a different machine in the target domain. Serious problems such as negative transfer may happen if the diagnostic knowledge learned from the source domain does not match the target domain. Therefore, it is of great practical value to have further investigation on the transfer between different machines in fault diagnosis in the future, and develop more novel appli-cations for accurate and efficient transfer. A robust neural network is important to improve the performance of model on diverse application scenarios [183]. However, most current works focus on extracting similar knowledge of the source and target domain data to improve the performance of transfer learning model, but neglect the importance of robust transfer learning models. Improving the robustness of transfer learning models would be promising direction to solve transfer between different machines' problems.

VII. CONCLUSION

This review has provided a comprehensive survey of the development of deep transfer learning-based bearing fault di-agnosis since 2016. A systematic guideline for researchers and practitioners who will begin or extend their works on bearing fault diagnosis is provided in detail, by covering the whole life cycle of deep transfer learning, including source domain data selection, data transformation, and transfer learning model selection. Seven open-source bearings datasets and commonly used data transformation methods have been introduced and discussed to provide researchers and practitioners with the choice of appropriate data selection and transformation. In addition, a novel taxonomy of deep transfer learning-based fault diagnosis methods from the perspective of target domain data properties divided by labels, machines, and faults has been provided, which can help researchers and practitioners efficiently find suitable deep transfer learning models based on the actual problems encountered in fault diagnosis. Finally, the research challenges and opportunities of future works have been discussed, including transferability assessment, transfer with abnormal data quality, multi-source transfer, incipient fault diagnosis, and novel applications in transfer between different machines. In summary, this review systematically expounds on the development of deep transfer learning-based

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bearing fault diagnosis since 2016, and provides valuable guidance for the research development and important implications for future practice in this field.

REFERENCES

[1] M. E. H. Benbouzid, "A review of induction motors signature analysis as a medium for faults detection," *IEEE Transactions on Industrial Electronics*, vol. 47, no. 5, pp. 984–993, 2000.

[2] Z. Chen and W. Li, "Multisensor feature fusion for bearing fault diagnosis using sparse autoencoder and deep belief network," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 7, pp. 1693–1702, 2017.

[3] X. He, Z. Wang, Y. Liu, and D. Zhou, "Least-squares fault detection and diagnosis for networked sensing systems using a direct state estimation approach," *IEEE Transactions on Industrial Informatics*, vol. 9, no. 3, pp. 1670–1679, 2013.

[4] Y. Ju, X. Tian, H. Liu, and L. Ma, "Fault detection of networked dynamical systems: a survey of trends and techniques," *International Journal of Systems Science*, vol. 52, no. 16, pp. 3390–3409, 2021.

[5] C. Li, J. V. de Oliveira, M. Cerrada, D. Cabrera, R. V. Sánchez, and G. Zurita, "A systematic review of fuzzy formalisms for bearing fault diagnosis," *IEEE Transactions on Fuzzy Systems*, vol. 27, no. 7, pp. 1362–1382, 2019.

[6] D. Hoang and H. Kang, "A survey on deep learning based bearing fault diagnosis," *Neurocomputing*, vol. 335, pp. 327–335, 2019.

[7] A. Rai and S. Upadhyay, "A review on signal processing techniques utilized in the fault diagnosis of rolling element bearings," *Tribology International*, vol. 96, pp. 289–306, 2016.

[8] P. Wen, X. Li, N. Hou, and S. Mu, "Distributed recursive fault estimation with binary encoding schemes over sensor networks," *Systems Science & Control Engineering*, vol. 10, no. 1, pp. 417–427, 2022.

[9] Q. Liu, Z. Wang, J. Zhang, and D. Zhou, "Necessary and sufficient conditions for fault diagnosability of linear open- and closed-loop stochastic systems under sensor and actuator faults," *IEEE Transactions on Automatic Control*, pp. 1–8, 2021.

[10] Y. Liu, Z. Wang, L. Zou, D. Zhou, and W. Chen, "Joint state and fault estimation of complex networks under measurement saturations and stochastic nonlinearities,"

[11] X. Ma, Y. Hu, M. Wang, F. Li, and Y. Wang, "Degradation state partition and compound fault diagnosis of rolling bearing based on personalized multi-label learning," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–11, 2021.

[12] K. Peng, K. Zhang, B. You, J. Dong, and Z. Wang, "A quality-based nonlinear fault diagnosis framework focusing on industrial multimode batch processes," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 4, pp. 2615–2624, 2016.

[13] S. Zhang, S. Zhang, B. Wang, and T. Habetler, "Machine learning and deep learning algorithms for bearing fault diagnostics—A comprehensive review," *arXiv preprint arXiv:1901.08247*, 2019.

[14] X. Chen, B. Zhang, and D. Gao, "Bearing fault diagnosis base on multi-scale CNN and LSTM model," *Journal of Intelligent Manufacturing*, vol. 32, pp. 971–987, 2021.

[15] S. Chen, R. Yang, and M. Zhong, "Graph-based semi-supervised random forest for rotating machinery gearbox fault diagnosis," *Control Engineering Practice*, vol. 117, 104952, 2021.

[16] Q. Lu, R. Yang, M. Zhong, and Y. Wang, "An improved fault diagnosis method of rotating machinery using sensitive features and RLS-BP neural network," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 4, pp. 1585–1593, 2019.

[17] Z. Yang, R. Yang, and M. Huang, "Rolling bearing incipient fault diagnosis method based on improved transfer learning with hybrid feature extraction," *Sensors*, vol. 21, no. 23, 7894, 2021

[18] R. Yang and M. Zhong, *Machine Learning-Based Fault Diagnosis for Industrial Engineering Systems*, CRC Press, 2022.

[19] Y. Zhang, R. Yang, M. Huang, Y. Han, Y. Wang, Y. Di, D. Su, and Q. Lu, "A simultaneous fault diagnosis method based on cohesion evaluation and improved BP-MLL for rotating machinery," *Shock and Vibration*, 2021.

[20] X. Han, Y. H. Liu, X. Zhang, Z. Zhang, and H. Yang, "Study on egg sorting model based on visible-near infrared spectroscopy," *Systems Science & Control Engineering*, vol. 10, no. 1, pp. 733–741, 2022.

[21] Y. Chen, Q. Song, Z. Zhao, Y. Liu, and F. E. Alsaadi, "Global mittag-leffler stability for fractional-order quaternion-valued neural networks with piecewise constant arguments and impulses," *International Journal of Systems Science*, vol. 53, no. 8, pp. 1756–1768, 2022.

[22] Y. Lei, B. Yang, X. Jiang, F. Jia, N. Li, and A. K. Nandi, "Applications of machine learning to machine fault diagnosis: A review and roadmap," *Mechanical Systems and Signal Processing*, vol. 138, p. 106587, 2020.

[23] B. Assaad, M. Eltabach, and J. Antoni, "Vibration based condition monitoring of a multistage epicyclic

gearbox in lifting cranes," *Mechanical Systems and Signal Processing*, vol. 42, no. 1-2, pp. 351–367, 2014.

[24] T. W. Rauber, F. De, Assis Boldt, and F. M. Varejao, "Heterogeneous feature models and feature selection applied to bearing fault diagnosis," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 1, pp. 637–646, 2015.

[25] Y. Yang, Y. Liao, G. Meng, and J. Lee, "A hybrid feature selection scheme for unsupervised learning and its application in bearing fault diagnosis," *Expert Systems with Applications*, vol. 38, no. 9, pp. 11 311–11 320, 2011.

[26] X. Yu, F. Dong, E. Ding, S. Wu, and C. Fan, "Rolling bearing fault diagnosis using modified LFDA and EMD with sensitive feature selection," *IEEE Access*, vol. 6, pp. 3715–3730, 2017.

[27] B. Yang, S. Xu, Y. Lei, C.G. Lee, E. Stewart, and C. Roberts, "Multi-source transfer learning network to complement knowledge for intelligent diagnosis of machines with unseen faults," *Mechanical Systems and Signal Processing*, vol. 162, p. 108095, 2022.

[28] K. Zhang, Y. Li, P. Scarf, and A. Ball, "Feature selection for high-dimensional machinery fault diagnosis data using multiple models and radial basis function networks," *Neurocomputing*, vol. 74, no. 17, pp. 2941–2952, 2011.

[29] W. Li, Y. Niu, and Z. Cao, "Event-triggered sliding mode control for multi-agent systems subject to channel fading," *International Journal of Systems Science*, vol. 53, no. 6, pp. 1233–1244, 2022.

[30] N. Zhang, L. Wu, J. Yang, and Y. Guan, "Naive bayes bearing fault diagnosis based on enhanced independence of data," *Sensors*, vol. 18, no. 2, p. 463, 2018.

[31] M. Amarnath, V. Sugumaran, and H. Kumar, "Exploiting sound signals for fault diagnosis of bearings using decision tree," *Measurement*, vol. 46, no. 3, pp. 1250–1256, 2013.

[32] P. Konar and P. Chattopadhyay, "Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs)," *Applied Soft Computing*, vol. 11, no. 6, pp. 4203–4211, 2011.

[33] J. Tian, C. Morillo, M. H. Azarian, and M. Pecht, "Motor bearing fault detection using spectral kurtosis-based feature extraction coupled with K-nearest neighbor distance analysis," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 3, pp. 1793–1803, 2015.

[34] Y. Yang, D. Yu, and J. Cheng, "A roller bearing fault diagnosis method based on EMD energy entropy and ANN," *Journal of Sound and Vibration*, vol. 294, no. 1-2, pp. 269–277, 2006.

[35] M. Yuwono, Y. Qin, J. Zhou, Y. Guo, B. G. Celler, and S. W. Su, "Automatic bearing fault diagnosis using particle swarm clustering and hidden Markov model," *Engineering Applications of Artificial Intelligence*, vol. 47, pp. 88–100, 2016.

[36] H. Shao, H. Jiang, H. Zhang, and T. Liang, "Electric locomotive bearing fault diagnosis using a novel convolutional deep belief network," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 3, pp. 2727–2736, 2017.

[37] C. M. Liang, Y. W. Li, Y. H. Liu, P. F. Wen, and H. Yang, "Segmentation and weight prediction of grape ear based on SFNet-ResNet18," *Systems Science & Control Engineering*, vol. 10, no. 1, pp. 722–732, 2022.

[38] D. Choi, J. Han, S. Park, and S. Hong, "Comparative study of CNN and RNN for motor fault diagnosis using deep learning," in *2020 IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA)*. IEEE, 2020, pp. 693–696.

[39] X. He, D. Wang, Y. Li, and C. Zhou, "A novel bearing fault diagnosis method based on Gaussian restricted Boltzmann machine," *Mathematical Problems in Engineering*, vol. 2016, 2016.

[40] X. Li, S. Feng, N. Hou, R. Wang, H. Li, M. Gao, and S. Li, "Surface microseismic data denoising based on sparse autoencoder and Kalman filter," *Systems Science & Control Engineering*, vol. 10, no. 1, pp. 616–628, 2022.

[41] H. Shao, H. Jiang, H. Zhao, and F. Wang, "A novel deep autoencoder feature learning method for rotating machinery fault diagnosis," *Mechanical Systems and Signal Processing*, vol. 95, pp. 187–204, 2017.

[42] C. Zhang, Y. He, L. Yuan, and S. Xiang, "Analog circuit incipient fault diagnosis method using DBN based features extraction," *IEEE Access*, vol. 6, pp. 23 053–23 064, 2018.

[43] T. Han, C. Liu, L. Wu, S. Sarkar, and D. Jiang, "An adaptive spatiotemporal feature learning approach for fault diagnosis in complex systems," *Mechanical Systems and Signal Processing*, vol. 117, pp. 170–187, 2019.

[44] C. Li, S. Zhang, Y. Qin, and E. Estupinan, "A systematic review of deep transfer learning for machinery fault diagnosis," *Neurocomputing*, vol. 407, pp. 121–135, 2020.

[45] F. Yao, Y. Ding, S. Hong and S.H. Yang, "A survey on evolved LoRa-based communication technologies for emerging internet of things applications," *International Journal of Network Dynamics and Intelligence*, vol. 1, no. 1, pp. 4–19, Dec. 2022.

[46] Z. Wan, R. Yang, M. Huang, N. Zeng, and X. Liu, "A review on transfer learning in EEG signal analysis," *Neurocomputing*, vol. 421, pp. 1–14, 2021.

[47] D. Xiao, Y. Huang, L. Zhao, C. Qin, H. Shi, and C. Liu, "Domain adaptive motor fault diagnosis using deep transfer learning," *IEEE Access*, vol. 7, pp. 80 937–80 949, 2019.

[48] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345–1359, 2009.

[49] P. Ma, H. Zhang, W. Fan, and C. Wang, "A diagnosis framework based on domain adaptation for bearing fault diagnosis across diverse domains," *ISA Transactions*, vol. 99, pp. 465–478, 2020.

[50] L. Wen, L. Gao, and X. Li, "A new deep transfer learning based on sparse auto-encoder for fault diagnosis," *IEEE Transactions on Systems, Man, and Cybernetics:*

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Systems, vol. 49, no. 1, pp. 136–144, 2017.

[51] L. Wan, Y. Li, K. Chen, K. Gong, and C. Li, "A novel deep convolution multi-adversarial domain adaptation model for rolling bearing fault diagnosis," *Measurement*, vol. 191, p. 110752, 2022.

[52] S. M. Abd Elrahman and A. Abraham, "A review of class imbalance problem,"*Journal of Network and Innovative Computing*, vol. 1, no. 2013, pp. 332–340, 2013.

[53] N. Yu, R. Yang and M. Huang, "Deep common spatial pattern based motor imagery classification with improved objective function," *International Journal of Network Dynamics and Intelligence*, vol. 1, no. 1, pp. 73–84, Dec. 2022.

[54] B. Zhao, X. Zhang, H. Li, and Z. Yang, "Intelligent fault diagnosis of rolling bearings based on normalized CNN considering data imbalance and variable working conditions," *Knowledge-Based Systems*, vol. 199, p. 105971, 2020.

[55] K. Weiss, T. M. Khoshgoftaar, and D. Wang, "A survey of transfer learning," *Journal of Big Data*, vol. 3, no. 1, pp. 1–40, 2016.

[56] F. Zhuang, Z. Qi, K. Duan, D. Xi, Y. Zhu, H. Zhu, H. Xiong, and Q. He, "A comprehensive survey on transfer learning," *Proceedings of the IEEE*, vol. 109, no. 1, pp. 43–76, 2020.

[57] R. Liu, B. Yang, E. Zio, and X. Chen, "Artificial intelligence for fault diagnosis of rotating machinery: A review," *Mechanical Systems and Signal Processing*, vol. 108, pp. 33–47, 2018.

[58] S. Zhang, S. Zhang, B. Wang, and T. G. Habetler, "Deep learning algorithms for bearing fault diagnostics—a comprehensive review," *IEEE Access*, vol. 8, pp. 29 857–29 881, 2020.

[59] H. Zheng, R. Wang, Y. Yang, J. Yin, Y. Li, Y. Li, and M. Xu, "Cross-domain fault diagnosis using knowledge transfer strategy: A review," *IEEE Access*, vol. 7, pp. 129 260–129 290, 2019.

[60] R. Yan, F. Shen, C. Sun, and X. Chen, "Knowledge transfer for rotary machine fault diagnosis," *IEEE Sensors Journal*, vol. 20, no. 15, pp. 8374–8393, 2019.

[61] Z. Zhao, Q. Zhang, X. Yu, C. Sun, S. Wang, R. Yan, and X. Chen, "Applications of unsupervised deep transfer learning to intelligent fault diagnosis: A survey and comparative study," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–28, 2021.

[62] W. Li, R. Huang, J. Li, Y. Liao, Z. Chen, G. He, R. Yan, and K. Gryllias, "A perspective survey on deep transfer learning for fault diagnosis in industrial scenarios: Theories, applications and challenges," *Mechanical Systems and Signal Processing*, vol. 167, p. 108487, 2022.

[63] X. Li, W. Zhang, H. Ma, Z. Luo, and X. Li, "Partial transfer learning in machinery cross-domain fault diagnostics using class-weighted adversarial networks," *Neural Networks*, vol. 129, pp. 313–322, 2020.

[64] S. F. Crone, S. Lessmann, and R. Stahlbock, "The impact of preprocessing on data mining: An evaluation of classifier sensitivity in direct marketing," *European Journal of Operational Research*, vol. 173, no. 3, pp. 781–800, 2006.

[65] S. Finlay, "Data transformation (pre-processing)," in *Credit Scoring, Response Modeling, and Insurance Rating*. Springer, 2012, pp. 144–164.

[66] M. Szankin and A. Kwasniewska, "Can AI see bias in X-ray images?" *International Journal of Network Dynamics and Intelligence*, vol. 1, no. 1, pp. 48–64, Dec. 2022.

[67] Y. Lei, M. J. Zuo, Z. He, and Y. Zi, "A multidimensional hybrid intelligent method for gear fault diagnosis," *Expert Systems with Applications*, vol. 37, no. 2, pp. 1419–1430, 2010.

[68] W. Qian, S. Li, and X. Jiang, "Deep transfer network for rotating machine fault analysis," *Pattern Recognition*, vol. 96, p. 106993, 2019.

[69] M. Sun, H. Wang, P. Liu, S. Huang, and P. Fan, "A sparse stacked denoising autoencoder with optimized transfer learning applied to the fault diagnosis of rolling bearings," *Measurement*, vol. 146, pp. 305–314, 2019.

[70] K. Zhao, H. Jiang, Z. Wu, and T. Lu, "A novel transfer learning fault diagnosis method based on manifold embedded distribution alignment with a little labeled data," *Journal of Intelligent Manufacturing*, pp. 1–15, 2020.

[71] Y. Zou, Y. Liu, J. Deng, Y. Jiang, and W. Zhang, "A novel transfer learning method for bearing fault diagnosis under different working conditions," *Measurement*, vol. 171, p. 108767, 2021.

[72] J. Si, H. Shi, J. Chen, and C. Zheng, "Unsupervised deep transfer learning with moment matching: A new intelligent fault diagnosis approach for bearings," *Measurement*, vol. 172, p. 108827, 2021.

[73] J. Shao, Z. Huang, and J. Zhu, "Transfer learning method based on adversarial domain adaption for bearing fault diagnosis," *IEEE Access*, vol. 8, pp. 119 421–119 430, 2020.

[74] F. M. Shakiba, M. Shojaee, S. M. Azizi and M. Zhou, "Real-time sensing and fault diagnosis for transmission lines," *International Journal of Network Dynamics and Intelligence*, vol. 1, no. 1, pp. 36–47, Dec. 2022.

[75] S. Shao, S. McAleer, R. Yan, and P. Baldi, "Highly accurate machine fault diagnosis using deep transfer learning," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2446–2455, 2019.

[76] J. Wang, Z. Mo, H. Zhang, and Q. Miao, "A deep learning method for bearing fault diagnosis based on time-frequency image," *IEEE Access*, vol. 7, pp. 42 373–42 383, 2019.

[77] D. Verstraete, A. Ferrada, E. L. Droguett, V. Meruane, and M. Modarres, "Deep learning enabled fault diagnosis using time-frequency image analysis of rolling element bearings," *Shock and Vibration*, vol. 2017, 2017.

[78] P. Cao, S. Zhang, and J. Tang, "Preprocessing-free gear fault diagnosis using small datasets with deep convolutional neural network-based transfer learning," *IEEE Access*, vol. 6, pp. 26 241–26 253, 2018.

[79] L. Wen, X. Li, and L. Gao, "A transfer convolutional neural network for fault diagnosis based on ResNet-50." *Neural Computing & Applications*, vol. 32, no. 10, 2020.

[80] D. Zhang and T. Zhou, "Deep convolutional neural network using transfer learning for fault diagnosis," *IEEE Access*, vol. 9, pp. 43 889–43 897, 2021.

[81] C. Che, H. Wang, Q. Fu, and X. Ni, "Deep transfer learning for rolling bearing fault diagnosis under variable operating conditions," *Advances in Mechanical Engineering*, vol. 11, no. 12, p. 1687814019897212, 2019.

[82] G. Xu, M. Liu, Z. Jiang, W. Shen, and C. Huang, "Online fault diagnosis method based on transfer convolutional neural networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 2, pp. 509–520, 2019.

[83] Z. Zheng, J. Fu, C. Lu, and Y. Zhu, "Research on rolling bearing fault diagnosis of small dataset based on a new optimal transfer learning network," *Measurement*, vol. 177, p. 109285, 2021.

[84] L. Wen, X. Li, X. Li, and L. Gao, "A new transfer learning based on VGG-19 network for fault diagnosis," in *2019 IEEE 23rd International Conference on Computer Supported Cooperative Work in Design (CSCWD)*. IEEE, 2019, pp. 205–209.

[85] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein *et al.*, "ImageNet large scale visual recognition challenge," *International Journal of Computer Vision*, vol. 115, no. 3, pp. 211–252, 2015.

[86] Y. Deng, D. Huang, S. Du, G. Li, C. Zhao, and J. Lv, "A double-layer attention based adversarial network for partial transfer learning in machinery fault diagnosis," *Computers in Industry*, vol. 127, p. 103399, 2021.

[87] M. J. Hasan, M. M. Islam, and J. Kim, "Acoustic spectral imaging and transfer learning for reliable bearing fault diagnosis under variable speed conditions," *Measurement*, vol. 138, pp. 620–631, 2019.

[88] X. Wang, C. Shen, M. Xia, D. Wang, J. Zhu, and Z. Zhu, "Multi-scale deep intra-class transfer learning for bearing fault diagnosis," *Reliability Engineering & System Safety*, vol. 202, p. 107050, 2020.

[89] B. Yang, Y. Lei, F. Jia, and S. Xing, "An intelligent fault diagnosis approach based on transfer learning from laboratory bearings to locomotive bearings," *Mechanical Systems and Signal Processing*, vol. 122, pp. 692–706, 2019.

[90] Y. Zhao, X. He, L. Ma, and H. Liu, "Unbiasedness-constrained least squares state estimation for time-varying systems with missing measurements under round-robin protocol," *International Journal of Systems Science*, pp. 1–17, 2022.

[91] K. A. Loparo, "Case western reserve university bearing data center," Bearings Vibration Data Sets, Case Western Reserve University, 2012: 22-28. Available: https://engineering.case.edu/bearingdatacenter

[92] E. Bechhoefer, "Condition based maintenance fault database for testing diagnostics and prognostic algorithms." MFPT Data, 2013. Available: https://www.mfpt.org/fault-data-sets/

[93] H. Huang and N. Baddour, "Bearing vibration data collected under time-varying rotational speed conditions," *Data in Brief*, vol. 21, pp. 1745–1749, 2018.

[94] C. Lessmeier, J. K. Kimotho, D. Zimmer, and W. Sextro, "Condition monitoring of bearing damage in electromechanical drive systems by using motor current signals of electric motors: A benchmark data set for data-driven classification," in *PHM Society European Conference*, vol. 3, no. 1, 2016.

[95] P. Nectoux, R. Gouriveau, K. Medjaher, E. Ramasso, B. Chebel-Morello, N. Zerhouni, and C. Varnier, "Pronostia: An experimental platform for bearings accelerated degradation tests." in *IEEE International Conference on Prognostics and Health Management, PHM'12*. IEEE Catalog Number: CPF12PHM-CDR, 2012, pp. 1–8.

[96] B. Wang, Y. Lei, N. Li, and N. Li, "A hybrid prognostics approach for estimating remaining useful life of rolling element bearings," *IEEE Transactions on Reliability*, vol. 69, no. 1, pp. 401–412, 2020.

[97] J. Lee, H. Qiu, G. Yu, J. Lin and and Rexnord Technical Services, "Bearing data set", NASA Ames Prognostics Data Repository, 2007. Available: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository

[98] Z. Chen, K. Gryllias, and W. Li, "Intelligent fault diagnosis for rotary machinery using transferable convolutional neural network," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 1, pp. 339–349, 2020.

[99] X. Li, H. Jiang, K. Zhao, and R. Wang, "A deep transfer nonnegativity-constraint sparse autoencoder for rolling bearing fault diagnosis with few labeled data," *IEEE Access*, vol. 7, pp. 91 216–91 224, 2019.

[100] Z. He, H. Shao, L. Jing, J. Cheng, and Y. Yang, "Transfer fault diagnosis of bearing installed in different machines using enhanced deep auto-encoder," *Measurement*, vol. 152, p. 107393, 2020.

[101] M. J. Hasan and J. Kim, "Bearing fault diagnosis under variable rotational speeds using stockwell transform-based vibration imaging and transfer learning," *Applied Sciences*, vol. 8, no. 12, p. 2357, 2018.

[102] B. Zhao, X. Zhang, Z. Zhan, and S. Pang, "Deep multi-scale convolutional transfer learning network: A novel method for intelligent fault diagnosis of rolling bearings under variable working conditions and domains," *Neurocomputing*, vol. 407, pp. 24–38, 2020.

[103] T. Han, C. Liu, W. Yang, and D. Jiang, "Learning transferable features in deep convolutional neural networks for diagnosing unseen machine conditions," *ISA Transactions*, vol. 93, pp. 341–353, 2019.

[104] K. Zhao, H. Jiang, X. Li, and R. Wang, "Ensemble adaptive convolutional neural networks with parameter transfer for rotating machinery fault diagnosis," *International Journal of Machine Learning and Cybernetics*, vol. 12, no. 5, pp. 1483–1499, 2021.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/TIM.2023.3244237, IEEE Transactions on Instrumentation and Measurement

21

[105] X. Li, Q. Song, Y. Liu, and F. E. Alsaadi, "Nash equilibrium and bang-bang property for the non-zero-sum differential game of multi-player uncertain systems with Hurwicz criterion," *International Journal of Systems Science*, pp. 1–12, 2022.

[106] X. Li, Q. Song, Z. Zhao, Y. Liu, and F. E. Alsaadi, "Optimal control and zero-sum differential game for Hurwicz model considering singular systems with multifactor and uncertainty," *International Journal of Systems Science*, vol. 53, no. 7, pp. 1416–1435, 2022.

[107] Z. Di, H. Shao, and J. Xiang, "Ensemble deep transfer learning driven by multisensor signals for the fault diagnosis of bevel-gear cross-operation conditions," *Science China Technological Sciences*, vol. 64, no. 3, pp. 481–492, 2021.

[108] H. Kim and B. D. Youn, "A new parameter repurposing method for parameter transfer with small dataset and its application in fault diagnosis of rolling element bearings," *IEEE Access*, vol. 7, pp. 46 917–46 930, 2019.

[109] R. Zhang, H. Tao, L. Wu, and Y. Guan, "Transfer learning with neural networks for bearing fault diagnosis in changing working conditions," *IEEE Access*, vol. 5, pp. 14 347–14 357, 2017.

[110] J. Wu, Z. Zhao, C. Sun, R. Yan, and X. Chen, "Few-shot transfer learning for intelligent fault diagnosis of machine," *Measurement*, vol. 166, p. 108202, 2020.

[111] X. Li, W. Zhang, and Q. Ding, "Cross-domain fault diagnosis of rolling element bearings using deep generative neural networks," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 7, pp. 5525–5534, 2018.

[112] E. Tzeng, J. Hoffman, N. Zhang, K. Saenko, and T. Darrell, "Deep domain confusion: Maximizing for domain invariance," *arXiv preprint arXiv:1412.3474*, 2014.

[113] X. Li, X. Jia, W. Zhang, H. Ma, Z. Luo, and X. Li, "Intelligent cross-machine fault diagnosis approach with deep auto-encoder and domain adaptation," *Neurocomputing*, vol. 383, pp. 235–247, 2020.

[114] Y. Zhou, Y. Dong, H. Zhou, and G. Tang, "Deep dynamic adaptive transfer network for rolling bearing fault diagnosis with considering cross-machine instance," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–11, 2021.

[115] Z. Wu, H. Jiang, T. Lu, and K. Zhao, "A deep transfer maximum classifier discrepancy method for rolling bearing fault diagnosis under few labeled data," *Knowledge-Based Systems*, vol. 196, p. 105814, 2020.

[116] Y. Ganin and V. Lempitsky, "Unsupervised domain adaptation by backpropagation," in *International Conference on Machine Learning*. PMLR, 2015, pp. 1180–1189.

[117] X. Wang, F. Liu, and D. Zhao, "Cross-machine fault diagnosis with semi-supervised discriminative adversarial domain adaptation," *Sensors*, vol. 20, no. 13, p. 3753, 2020.

[118] T. Han, C. Liu, R. Wu, and D. Jiang, "Deep transfer learning with limited data for machinery fault diagnosis," *Applied Soft Computing*, vol. 103, p. 107150, 2021.

[119] X. Li, W. Zhang, Q. Ding, and X. Li, "Diagnosing rotating machines with weakly supervised data using deep transfer learning," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 3, pp. 1688–1697, 2019.

[120] L. Guo, Y. Lei, S. Xing, T. Yan, and N. Li, "Deep convolutional transfer learning network: A new method for intelligent fault diagnosis of machines with unlabeled data," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 9, pp. 7316–7325, 2018.

[121] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in *International Conference on Machine Learning*. PMLR, 2015, pp. 448–456.

[122] M. Long, J. Wang, G. Ding, J. Sun, and P. S. Yu, "Transfer feature learning with joint distribution adaptation," in *Proceedings of the IEEE International Conference on Computer Vision*, 2013, pp. 2200–2207.

[123] M. Kim, J. U. Ko, J. Lee, B. D. Youn, J. H. Jung, and K. H. Sun, "A domain adaptation with semantic clustering (DASC) method for fault diagnosis of rotating machinery," *ISA Transactions*, vol. 120, pp. 372–382, 2022.

[124] S. Jia, Y. Deng, J. Lv, S. Du, and Z. Xie, "Joint distribution adaptation with diverse feature aggregation: A new transfer learning framework for bearing diagnosis across different machines," *Measurement*, vol. 187, p. 110332, 2022.

[125] Z. Wu, H. Jiang, K. Zhao, and X. Li, "An adaptive deep transfer learning method for bearing fault diagnosis," *Measurement*, vol. 151, p. 107227, 2020.

[126] X. Cao, Y. Wang, B. Chen, and N. Zeng, "Domain-adaptive intelligence for fault diagnosis based on deep transfer learning from scientific test rigs to industrial applications," *Neural Computing and Applications*, vol. 33, no. 9, pp. 4483–4499, 2021.

[127] X. Li, H. Jiang, M. Xie, T. Wang, R. Wang, and Z. Wu, "A reinforcement ensemble deep transfer learning network for rolling bearing fault diagnosis with multi-source domains," *Advanced Engineering Informatics*, vol. 51, p. 101480, 2022.

[128] Y. Zhang, Z. Ren, S. Zhou, K. Feng, K. Yu, and Z. Liu, "Supervised contrastive learning-based domain adaptation network for intelligent unsupervised fault diagnosis of rolling bearing," *IEEE/ASME Transactions on Mechatronics*, vol. 27, no. 6, pp. 5371–5380, 2022.

[129] N. Lu, H. Hu, T. Yin, Y. Lei, and S. Wang, "Transfer relation network for fault diagnosis of rotating machinery with small data," *IEEE Transactions on Cybernetics*, 2021.

[130] Y. Liu, Y. Wang, T. W. Chow, and B. Li, "Deep adversarial subdomain adaptation network for intelligent fault diagnosis," *IEEE Transactions on Industrial Informatics*, vol. 18, pp. 6038–6046, 2022.

[131] Y. Dong, Y. Li, H. Zheng, R. Wang, and M. Xu, "A new dynamic model and transfer learning based intelligent fault diagnosis framework for rolling element bearings race faults: Solving the small sample problem," *ISA Transactions*, 2021.

[132] W. Lu, B. Liang, Y. Cheng, D. Meng, J. Yang, and

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIM.2023.3244237, IEEE Transactions on Instrumentation and Measurement

22

T. Zhang, "Deep model based domain adaptation for fault diagnosis," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 3, pp. 2296–2305, 2016.

[133] X. Li, Y. Hu, J. Zheng, M. Li, and W. Ma, "Central moment discrepancy based domain adaptation for intelligent bearing fault diagnosis," *Neurocomputing*, vol. 429, pp. 12–24, 2021.

[134] Y. Xia, C. Shen, D. Wang, Y. Shen, W. Huang, and Z. Zhu, "Moment matching-based intraclass multisource domain adaptation network for bearing fault diagnosis," *Mechanical Systems and Signal Processing*, vol. 168, p. 108697, 2022.

[135] W. Qian, S. Li, and J. Wang, "A new transfer learning method and its application on rotating machine fault diagnosis under variant working conditions," *IEEE Access*, vol. 6, pp. 69 907–69 917, 2018.

[136] Z. Zhang, H. Chen, S. Li, and Z. An, "Unsupervised domain adaptation via enhanced transfer joint matching for bearing fault diagnosis," *Measurement*, vol. 165, p. 108071, 2020.

[137] P. Chen, R. Zhao, T. He, K. Wei, and Q. Yang, "Unsupervised domain adaptation of bearing fault diagnosis based on join sliced Wasserstein distance," *ISA Transactions*, vol. 129, pp. 504–519,2022.

[138] S. Yang, X. Kong, Q. Wang, Z. Li, H. Cheng, and K. Xu, "Deep multiple auto-encoder with attention mechanism network: A dynamic domain adaptation method for rotary machine fault diagnosis under different working conditions," *Knowledge-Based Systems*, vol. 249, p. 108639, 2022.

[139] H. Chen, C. Wu, B. Du, and L. Zhang, "DSDANet: Deep Siamese domain adaptation convolutional neural network for cross-domain change detection," *arXiv preprint arXiv:2006.09225*, 2020.

[140] B. Zhang, W. Li, X. Li, and S. Ng, "Intelligent fault diagnosis under varying working conditions based on domain adaptive convolutional neural networks," *IEEE Access*, vol. 6, pp. 66 367–66 384, 2018.

[141] T. Han, C. Liu, W. Yang, and D. Jiang, "Deep transfer network with joint distribution adaptation: A new intelligent fault diagnosis framework for industry application," *ISA Transactions*, vol. 97, pp. 269–281, 2020.

[142] W. Qian, S. Li, P. Yi, and K. Zhang, "A novel transfer learning method for robust fault diagnosis of rotating machines under variable working conditions," *Measurement*, vol. 138, pp. 514–525, 2019.

[143] S. Pang and X. Yang, "A cross-domain stacked denoising autoencoders for rotating machinery fault diagnosis under different working conditions," *IEEE Access*, vol. 7, pp. 77 277–77 292, 2019.

[144] S. Kang, C. Qiao, Y. Wang, Q. Wang, M. Hu, and V. Mikulovich, "Fault diagnosis method of rolling bearings under varying working conditions based on deep feature transfer," *Journal of Mechanical Science and Technology*, vol. 34, no. 11, pp. 4383–4391, 2020.

[145] J. Tian, D. Han, M. Li, and P. Shi, "A multi-source information transfer learning method with subdomain adaptation for cross-domain fault diagnosis," *Knowledge-Based Systems*, vol. 243, p. 108466, 2022.

[146] C. Cheng, B. Zhou, G. Ma, D. Wu, and Y. Yuan, "Wasserstein distance based deep adversarial transfer learning for intelligent fault diagnosis with unlabeled or insufficient labeled data," *Neurocomputing*, vol. 409, pp. 35–45, 2020.

[147] T. Han, C. Liu, W. Yang, and D. Jiang, "A novel adversarial learning framework in deep convolutional neural network for intelligent diagnosis of mechanical faults," *Knowledge-Based Systems*, vol. 165, pp. 474–487, 2019.

[148] M. Zhang, D. Wang, W. Lu, J. Yang, Z. Li, and B. Liang, "A deep transfer model with Wasserstein distance guided multi-adversarial networks for bearing fault diagnosis under different working conditions," *IEEE Access*, vol. 7, pp. 65 303–65 318, 2019.

[149] N. Xu and X. Li, "Cross-domain machinery fault diagnosis using adversarial network with conditional alignments," in *2019 Prognostics and System Health Management Conference (PHM-Qingdao)*. IEEE, 2019, pp. 1–5.

[150] N. Xu and X. Li, "Intelligent fault diagnosis methodology under varying operating conditions using multilayer domain adversarial learning strategy," *International Journal of Dynamics and Control*, pp. 1–11, 2021.

[151] J. Jiao, J. Lin, M. Zhao, and K. Liang, "Double-level adversarial domain adaptation network for intelligent fault diagnosis," *Knowledge-Based Systems*, vol. 205, p. 106236, 2020.

[152] B. Xia, K. Wang, A. Xu, P. Zeng, N. Yang, and B. Li, "Intelligent fault diagnosis for bearings of industrial robot joints under varying working conditions based on deep adversarial domain adaptation," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–13, 2022.

[153] M. Deng, A. Deng, Y. Shi, and M. Xu, "Correlation regularized conditional adversarial adaptation for multitarget-domain fault diagnosis," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 12, pp. 8692–8702, 2022.

[154] Z. Fan, Q. Xu, C. Jiang, and S. X. Ding, "Weighted quantile discrepancy-based deep domain adaptation network for intelligent fault diagnosis," *Knowledge-Based Systems*, vol. 240, p. 108149, 2022.

[155] Z. Wu, H. Zhang, J. Guo, Y. Ji, and M. Pecht, "Imbalanced bearing fault diagnosis under variant working conditions using cost-sensitive deep domain adaptation network," *Expert Systems with Applications*, vol. 193, p. 116459, 2022.

[156] F. Li, T. Tang, B. Tang, and Q. He, "Deep convolution domain-adversarial transfer learning for fault diagnosis of rolling bearings," *Measurement*, vol. 169, pp. 108339, 2021.

[157] H. Liu, J. Zhou, Y. Xu, Y. Zheng, X. Peng, and W. Jiang, "Unsupervised fault diagnosis of rolling bearings using a deep neural network based on generative adversarial networks," *Neurocomputing*, vol. 315, pp. 412–424,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIM.2023.3244237, IEEE Transactions on Instrumentation and Measurement.

23

2018.

[158] Y. Z. Liu, K. M. Shi, Z. X. Li, G. F. Ding, and Y. S. Zou, "Transfer learning method for bearing fault diagnosis based on fully convolutional conditional Wasserstein adversarial networks," *Measurement*, vol. 180, p. 109553, 2021.

[159] A. Zhang, S. Li, Y. Cui, W. Yang, R. Dong, and J. Hu, "Limited data rolling bearing fault diagnosis with few-shot learning," *IEEE Access*, vol. 7, pp. 110 895–110 904, 2019.

[160] Y. Gao, L. Gao, X. Li, and Y. Zheng, "A zero-shot learning method for fault diagnosis under unknown working loads," *Journal of Intelligent Manufacturing*, vol. 31, no. 4, pp. 899–909, 2020.

[161] Q. Qian, Y. Qin, Y. Wang, and F. Liu, "A new deep transfer learning network based on convolutional auto-encoder for mechanical fault diagnosis," *Measurement*, vol. 178, p. 109352, 2021.

[162] J. Li, R. Huang, and W. Li, "Intelligent fault diagnosis for bearing dataset using adversarial transfer learning based on stacked auto-encoder," *Procedia Manufacturing*, vol. 49, pp. 75–80, 2020.

[163] W. Zhang, X. Li, H. Ma, Z. Luo, and X. Li, "Open-set domain adaptation in machinery fault diagnostics using instance-level weighted adversarial learning," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 11, pp. 7445–7455, 2021.

[164] W. Zhang, X. Li, H. Ma, Z. Luo, and X. Li, "Universal domain adaptation in fault diagnostics with hybrid weighted deep adversarial learning," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 12, pp. 7957–7967, 2021.

[165] S. Zhao, X. Yue, S. Zhang, B. Li, H. Zhao, B. Wu, R. Krishna, J. E. Gonzalez, A. L. Sangiovanni-Vincentelli, S. A. Seshia, and K. Keutzer, "A review of single-source deep unsupervised visual domain adaptation," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 2, pp. 473–493, 2022.

[166] C. Qian, J. Zhu, Y. Shen, Q. Jiang, and Q. Zhang, "Deep transfer learning in mechanical intelligent fault diagnosis: application and challenge," *Neural Processing Letters*, pp. 1–23, 2022.

[167] Z. Wang, Z. Dai, B. Póczos, and J. Carbonell, "Characterizing and avoiding negative transfer," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 11 293–11 302.

[168] W. Zhang, L. Deng, L. Zhang, and D. Wu, "Overcoming negative transfer: A survey," *arXiv preprint arXiv:2009.00909*, 2020.

[169] G. Zhao, Y. Li and Q. Xu, "From emotion AI to cognitive AI," *International Journal of Network Dynamics and Intelligence*, vol. 1, no. 1, pp. 65–72, Dec. 2022.

[170] B. Yang, Y. Lei, S. Xu, and C. Lee, "An optimal transport-embedded similarity measure for diagnostic knowledge transferability analytics across machines," *IEEE Transactions on Industrial Electronics*, 2021.

[171] L. Ciabattoni, F. Ferracuti, A. Freddi, and A. Monteriu, "Statistical spectral analysis for fault diagnosis of rotating machines," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 5, pp. 4301–4310, 2017.

[172] J. Hu, C. Jia, H. Liu, X. Yi, and Y. Liu, "A survey on state estimation of complex dynamical networks," *International Journal of Systems Science*, vol. 52, no. 16, pp. 3351–3367, 2021.

[173] Y. Luo, Z. Wang, and G. Wei, "Fault detection for fuzzy systems with multiplicative noises under periodic communication protocols," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 4, pp. 2384–2395, 2018.

[174] J. Mao, Y. Sun, X. Yi, H. Liu, and D. Ding, "Recursive filtering of networked nonlinear systems: A survey," *International Journal of Systems Science*, vol. 52, no. 6, pp. 1110–1128, 2021.

[175] D. Zhou, Y. Zhao, Z. Wang, X. He, and M. Gao, "Review on diagnosis techniques for intermittent faults in dynamic systems," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 3, pp. 2337–2347, 2020.

[176] L. Zou, Z. Wang, J. Hu, Y. Liu, and X. Liu, "Communication-protocol-based analysis and synthesis of networked systems: Progress, prospects and challenges," *International Journal of Systems Science*, vol. 52, no. 14, pp. 3013–3034, 2021.

[177] H. Geng, Z. Wang, Y. Chen, F. E. Alsaadi, and Y. Cheng, "Multi-sensor filtering fusion with parametric uncertainties and measurement censoring: Monotonicity and boundedness," *IEEE Transactions on Signal Processing*, vol. 69, pp. 5875–5890, 2021.

[178] H. Geng, H. Liu, L. Ma, and X. Yi, "Multi-sensor filtering fusion meets censored measurements under a constrained network environment: advances, challenges and prospects," *International Journal of Systems Science*, vol. 52, no. 16, pp. 3410–3436, 2021.

[179] F. Qu, X. Zhao, X. Wang, and E. Tian, "Probabilistic-constrained distributed fusion filtering for a class of time-varying systems over sensor networks: A torus-event-triggering mechanism," *International Journal of Systems Science*, vol. 53, no. 6, pp. 1288–1297, 2022.

[180] G. Ahn, H. Lee, J. Park, and S. Hur, "Development of indicator of data sufficiency for feature-based early time series classification with applications of bearing fault diagnosis," *Processes*, vol. 8, no. 7, 2020.

[181] Q. He, J. Wang, Y. Liu, D. Dai, and F. Kong, "Multi-scale noise tuning of stochastic resonance for enhanced fault diagnosis in rotating machines," *Mechanical Systems and Signal Processing*, vol. 28, pp. 443–457, 2012.

[182] W. Mao, L. Ding, S. Tian, and X. Liang, "Online detection for bearing incipient fault based on deep transfer learning," *Measurement*, vol. 152, p. 107278, 2020.

[183] S. Zheng, Y. Song, T. Leung, and I. Goodfellow, "Improving the robustness of deep neural networks via stability training," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 4480–4488.