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Review article

Domain generalization for rotating machinery fault diagnosis: A survey

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ABSTRACT

Distribution shift significantly hampers the performance of deep fault diagnostic models in real-world applications, prompting an increased focus on transfer learning-based fault diagnosis. Domain adaptation (DA) and domain generalization (DG), two unsupervised versions of transfer learning, are particularly noteworthy. Unlike DA, which necessitates the availability of unlabeled data from the target domain, DG operates without this requirement, enhancing its flexibility and applicability across various scenarios. Since DG was first applied to fault diagnosis in 2020, a proliferation of DG-based diagnostic methods has emerged, sparking a need for a comprehensive review. This paper aims to fill this gap by surveying these methods, categorizing existing studies by task type and methodology type in turn, and analyzing and expanding upon the approaches within each category. This paper also offers baseline accuracy for several notable methods, serving as a useful reference. Furthermore, an algorithmic framework that integrates various DG approaches is released to aid researchers in replicating our experiments and developing their methodologies. This paper not only augments existing literature but also equips scholars with practical tools and insights to advance the field of DG fault diagnosis. The code is available at https://github.com/xiaoyiming1999/DG-for-RMFD.

1. Introduction

Distribution shift, where training and test data follow similar but distinct distributions, is a significant challenge in deploying deep models in real-world settings [1,2]. In the context of rotating machinery fault diagnosis, distribution shift usually occurs when the training and test data are collected under varying operating conditions, or on different but related machines [3–5].

A simple solution to the distribution shift problem is initial transfer learning (TL), which uses a small amount of target-domain labeled data to fine-tune the model trained on source domains [6–9]. However, labeling the target data is often time-consuming and laborious, thus motivating two unsupervised versions of TL, i.e., domain adaptation (DA) [10–15] and domain generalization (DG) [16–21]. Although DA does not require labeled target-domain data, it still requires that unlabeled data in the target domain be available and used for training. Considering that the target data of each class is usually difficult to obtain in advance due to factors such as cost and safety, DA is more suitable for offline fault diagnosis. In contrast, DG removes these limitations by using only source-domain data to train the model, while target-domain data appears only in the inference phase. This out-of-the-box property of DG models makes them well-suited for online health monitoring of machines and hence has attracted widespread attention from scholars.

Since the first application of DG technology to fault diagnosis in 2020, scholars have successively conducted many impressive DG fault diagnostic studies. The task types have been expanded from the initial multi-source DG to single-source DG, semi-supervised DG, open DG, etc. The design strategies of their methods have also evolved, from aligning source domains to capture domain-invariant features, to enabling the model to learn to process distribution-shifted data via *meta*-learning, to augmenting domains with sample generation, to name a few. These developments have greatly enriched the field of DG fault diagnosis and motivated this paper to provide a comprehensive survey of it.

Since 2019, several papers [22–29] have been published with the same aim as this paper to investigate solutions to the distribution shift problem in fault diagnosis. However, [22–26] focus more on giving an overall overview of the field of TL-based fault diagnosis without highlighting the branch of unsupervised TL, and thus may omit detailed information about this branch. Furthermore, even though [27], and [28] discuss unsupervised TL, their emphasis is on DA, and they usually gloss over or even do not mention DG. In 2024, Zhao *et al.* [29] firstly surveyed the many DG fault diagnosis methods from a task-type-oriented

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perspective and conducted a comparative study on ten datasets, which can serve as an important reference for subsequent studies. Although this paper similarly categorizes existing DG fault diagnosis methods based on task type in general, it makes a further methodology-type-based distinction between the methods under each task type. For each DG task, this paper extends some potential methods rather than limiting the discussion to existing methods. Moreover, the code published in this paper includes some methods not covered in the code of [29], such as *meta*-learning and ensemble learning. There are also some surveys on DG [1,2] in the field of computer vision (CV), which present detailed theoretical descriptions of various categories of DG methods. However, they do not provide insights into the emerging DG tasks such as federated DG, semi-supervised DG, and open DG. The baseline accuracy reported in them and the published code may also not be appropriate for fault diagnosis research to reference. This paper complements the above surveys with the following main contributions:

(1) It categorizes the existing DG fault diagnosis studies by task type in general, and further subdivides the studies under each task according to the methodology type, providing an in-depth review and summary of existing solutions and suggestions for additional extensions of these methods.

(2) It evaluates the performance of several prominent DG methods using two publicly accessible fault diagnosis datasets, contributing valuable empirical evidence to the field.

(3) An algorithm framework that integrates various DG methods is released for the academic community to reproduce our experiments. The extended interface retained by the framework also allows scholars to develop new methods and load their own datasets conveniently. Our code can be acquired at https://github.com/xiaoyiming1999/DG-for-RMFD.

The remainder of this paper is organized as follows: Section 2 briefly describes the task-type-driven taxonomy of DG studies and mathematically defines each DG task. Section 3 comprehensively reviews, summarizes and extends the solutions under each DG task. Section 4 shows the experimental setup and reports the baseline accuracy of some DG methods. Section 5 discusses future research directions. Section 6 concludes this paper.

2. Background

We first briefly introduce some common notations according to the existing references [1,2]. Let $\mathscr{X}$ be the input space, and $\mathscr{Y}$ be the label space, a domain can be defined as $\mathscr{D} = \{(x,y)\} \sim p(X,Y)$, where x is a sample drawn from $\mathscr{X}$, y is its corresponding label drawn from $\mathscr{Y}$, X is the union of all samples, Y is the union of all labels, and $p(X,Y)$ is a joint distribution of the input samples and output labels. This distribution can be decomposed into $p(X,Y) = p(X)p(Y|X)$, where $p(X)$ is a marginal distribution on X, and $p(Y|X)$ is a posterior distribution of Y given X. The goal of DG is to learn a prediction function $H(\cdot) = (G^{\circ}F)(\cdot) : \mathscr{X} \rightarrow \mathscr{Y}$ with the lowest possible prediction error on an unseen target domain using only the source domain(s), where $F(\cdot)$ is a representation learning function, $G(\cdot)$ is a classification function, and $^{\circ}$ represents composite mapping. The notations used frequently in this paper are listed in Table 1.

Table 1
Notations used in this paper.

Notation	Description	Notation	Description
x,y,d	Sample/label/domain label	$F(\cdot)$	Feature extractor
x',y',d'	Generated sample/label/ domain label	$G(\cdot)$	Classifier
$\mathscr{D}$	Domain	$D(\cdot)$	Domain discriminator
$\mathbb{E}$	Expectation	$H(\cdot)$	Prediction function
$\mathscr{L}(\cdot,\cdot)$	Loss function	K	Number of source domains
$M(\cdot)$	Generator	C	Number of known classes

Based on the task type, this paper divides the existing DG fault diagnosis studies into six groups: multi-source DG, single-source DG, semi-supervised DG, open DG, imbalance DG, and federated DG. Fig. 1 illustrates their objectives and Table 2 distinguishes between them. In addition, Fig. 2 illustrates the trend of growth in the number of DG fault diagnosis studies under each task in recent years, and Fig. 3 shows the number of studies under each task as a percentage of the total. These statistics are from the literature database Web of Science. By searching with the keywords “Fault diagnosis” and “Domain generalization” and restricting the literature type to “Article”, a total of 70 articles on DG fault diagnosis for rotating machinery such as bearings, gearboxes, etc. are found as the main research objects of this paper. Moreover, one article on pipelines, one article on brake pads for high-speed trains, and one article on chiller are also included in the scope of this paper. However, those that focus on alternating current motors, chemical processes, nuclear power plants, etc., are not considered in this paper. In the process of literature search, there may be omissions due to incomplete or inaccurate keywords. For example, some scholars use “Cross domain” as a keyword instead of “Domain generalization”, which is a major threat to the effectiveness of literature search. As can be seen in Figs. 2 and 3, the number of DG fault diagnosis studies, especially those for emerging DG tasks, is increasing every year. This indicates that DG fault diagnosis is an important research area and will continue to receive attention for some years to come.

Multi-source DG, as shown in Fig. 1**a**, is the most frequently adopted task setting in existing DG fault diagnosis studies. In this task, we can access K ($K > 1$) similar but distinct labeled source domains $\mathscr{D}_{\mathscr{S}} = \{\mathscr{D}_k = \{(x^{(k)},y^{(k)})\}\}_{k=1}^{K}$, each associated with a joint distribution $p(X^{(k)}, Y^{(k)})$, and $(x^{(k)},y^{(k)})$ is a sample-label pair drawn from it. For any $k \neq k'$ and $k,k' \in \{1,2,...,K\}$, we have $p(X^{(k)}, Y^{(k)}) \neq p(X^{(k')}, Y^{(k')})$. The joint distribution associated with the target domain $\mathscr{D}_{\mathscr{T}} = \{x^{\mathscr{T}}\}$ is denoted by $p(X^{\mathscr{T}}, Y^{\mathscr{T}})$. Also, $p(X^{(k)}, Y^{(k)}) \neq p(X^{\mathscr{T}}, Y^{\mathscr{T}})$ for any $k \in \{1,2,...,K\}$. Such differences are usually attributed to shift in the marginal distribution $p(X)$, whereas the posterior distribution $p(Y|X)$ is stable across domains. In the context of fault diagnosis, the factors contributing to the shift in $p(X)$ include variations in rotational speed and load on the same machine and differences between the mechanical structures of different machines, etc. The source and target domains share the same label set $\mathscr{C} = \{0,1,...,C-1\}$, where C is the number of known classes, label 0 indicates the normal class, and the remaining labels indicate the fault classes. For any domain, there is $N_0 = N_1 = ... = N_{C-1}$, where N_0 is the number of samples for the normal class in any domain, and so on. As mentioned in [30], DG was proposed precisely to learn on multiple source domains to capture the invariant features, motivated by the fact that the features can be generalized to unseen target domains. This task setting is intuitive and favored by scholars, and our experimental study in Section 4 will follow this setting. All other DG tasks beyond this are extensions of this task.

Single-source DG differs from the multi-source DG in that it assumes that only one source domain is available, i.e., $K = 1$, as shown in Fig. 1**b**. When there are multiple source domains available but no domain labels, it can also be considered as a single-source DG. Moreover, in the context of fault diagnosis, single-source DG can be further extended to only allow access to data collected under continuously varying conditions [31], which are difficult to distinguish into multiple domains.

Semi-supervised DG is a task that assumes that samples from multiple source domains are available but only samples from one source domain are labeled, i.e., $\mathscr{D}_{\mathscr{S}} = \{\mathscr{D}_1 = \{(x^{(1)},y^{(1)})\}, \mathscr{D}_2 = \{(x^{(2)})\}, ..., \mathscr{D}_K = \{(x^{(K)})\}\}$. Note that semi-supervised DG emphasizes that the source-domain samples are not fully labeled, which does not conflict with unsupervised TL referring to the target-domain samples being unlabeled. As shown in Fig. 1**c**, semi-supervised DG aims to capture domain-invariant features between labeled and unlabeled source domains.

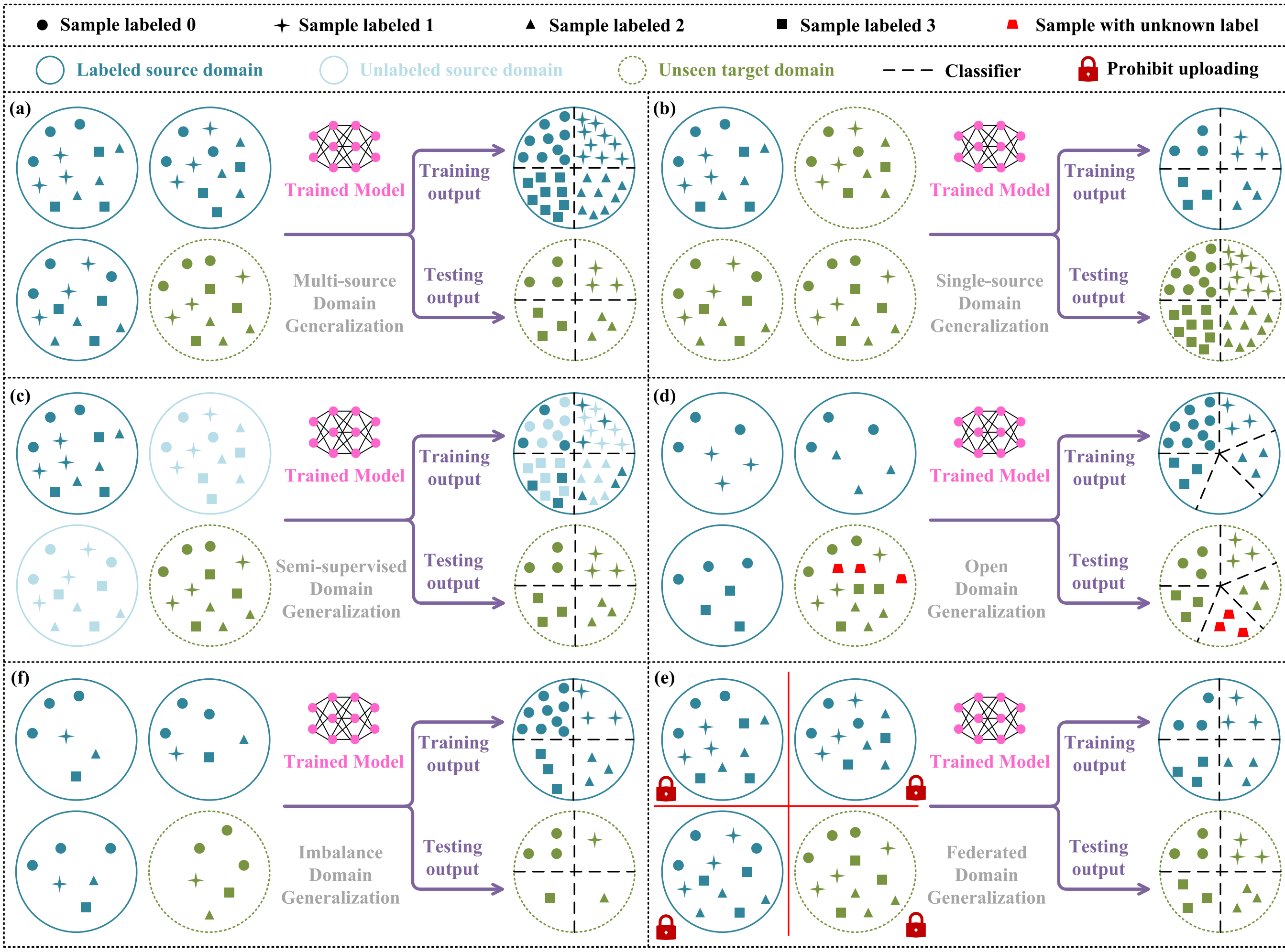

Fig. 1. Illustration of various DG fault diagnosis tasks: (a) multi-source DG; (b) single-source DG; (c) semi-supervised DG; (d) open DG; (e) Imbalance DG; (f) Federated DG.

Table 2
Distinctions between different DG tasks.

Tasks	Source domain(s)	Available labels	Label set per domain	Number of samples per class	data storage
Multi-source DG	$\mathscr{D}_1, \mathscr{D}_2, \ldots, \mathscr{D}_K$	$Y^{(1)}, Y^{(2)}, \ldots Y^{(K)}$	$\mathscr{C}^{(1)} = \mathscr{C}^{(2)} = \ldots = \mathscr{C}^{(K)} = \mathscr{C}^{\mathscr{T}}$	$N_0 = N_1 = \ldots = N_{C-1}$	Centralized
Single-source DG	$\mathscr{D}_1$	$Y^{(1)}$	$\mathscr{C}^{(1)} = \mathscr{C}^{\mathscr{T}}$	$N_0 = N_1 = \ldots = N_{C-1}$	Centralized
Semi-supervised DG	$\mathscr{D}_1, \mathscr{D}_2, \ldots, \mathscr{D}_K$	$Y^{(1)}$	$\mathscr{C}^{(1)} = \mathscr{C}^{(2)} = \ldots = \mathscr{C}^{(K)} = \mathscr{C}^{\mathscr{T}}$	$N_0 = N_1 = \ldots = N_{C-1}$	Centralized
Open DG	$\mathscr{D}_1, \mathscr{D}_2, \ldots, \mathscr{D}_K$	$Y^{(1)}, Y^{(2)}, \ldots Y^{(K)}$	$\mathscr{C}^{(1)} \neq \mathscr{C}^{(2)} \neq \ldots \neq \mathscr{C}^{(K)} \subseteq \mathscr{C}^{\mathscr{T}}$	$N_0 = N_i, i \in \{1, 2, \ldots, C-1\}$	Centralized
Imbalance DG	$\mathscr{D}_1, \mathscr{D}_2, \ldots, \mathscr{D}_K$	$Y^{(1)}, Y^{(2)}, \ldots Y^{(K)}$	$\mathscr{C}^{(1)} = \mathscr{C}^{(2)} = \ldots = \mathscr{C}^{(K)} = \mathscr{C}^{\mathscr{T}}$	$N_0 \gg N_1 = \ldots = N_{C-1}$	Centralized
Federated DG	$\mathscr{D}_1, \mathscr{D}_2, \ldots, \mathscr{D}_K$	$Y^{(1)}, Y^{(2)}, \ldots Y^{(K)}$	$\mathscr{C}^{(1)} = \mathscr{C}^{(2)} = \ldots = \mathscr{C}^{(K)} = \mathscr{C}^{\mathscr{T}}$	$N_0 = N_1 = \ldots = N_{C-1}$	Distributed

Open DG is a challenging task, which assumes that the source domains do not hold the same label set and the label set of the target domain contains new labels that are not present in all the source domains, i.e., $\mathscr{C}^{(1)} \neq \mathscr{C}^{(2)} \neq \ldots \neq \mathscr{C}^{(K)} \subseteq \mathscr{C}^{\mathscr{T}}$. This setting was first proposed in [18]. In the context of fault diagnosis, it is usually easy to collect vibration signals from machines in their normal state, so each source domain should contain at least samples from the normal class. As shown in Fig. 1**d**, open DG requires not only to learn generalizable representations on these source domains to classify target-domain samples of known classes but also to reject samples of unknown classes.

Imbalance DG introduces the class imbalance problem [32–36] which is common in fault diagnosis to DG. Since the machines operate predominantly under normal states, the number of samples from the normal class is usually much higher than the number of samples from the fault classes. Therefore, for any domain, $N_0 \gg N_1 = \ldots = N_{C-1}$, as shown in Fig. 1**e**. In imbalance DG, it is not only necessary to address the distribution shift problem, but also the problem of the model's tendency to recognize fault classes as normal class due to the long-tail effect.

Federated DG, as shown in Fig. 1**f**, aims to address the DG problem in the framework of federated learning (FL) [37–40], where data is no longer stored centrally but distributed across multiple clients and each client holds a domain. The source clients (holders of source domains) are required to collaboratively train a diagnostic model that can be used by the target clients (holders of unseen target domains), provided that the local data does not leave the local storage to protect its privacy. Since traditional DG methods usually require directly manipulating data or representations, and the distribution shift problem can cause the local optimization objectives to shift from the global optimization objective in FL [41–44], federated DG poses a higher challenge for both DG research and FL research.

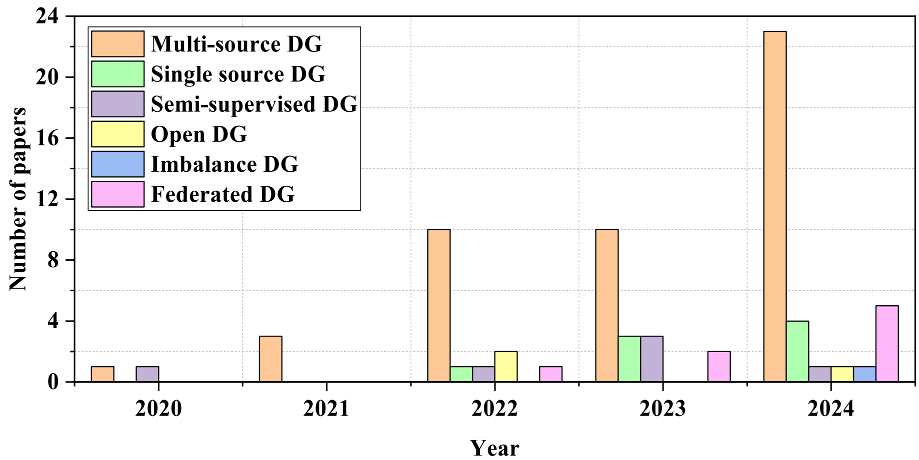

Fig. 2. Number of papers on DG fault diagnosis in recent years searchable on Web of Science as of July 2024.

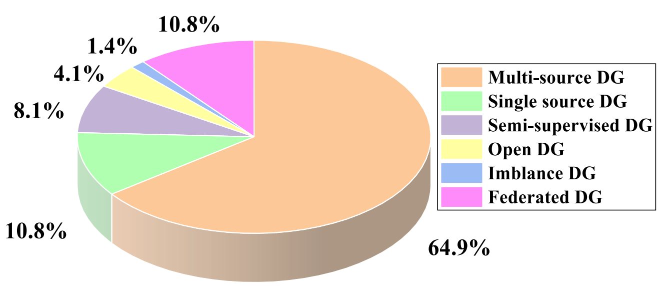

Fig. 3. Number of DG fault diagnosis studies under each task as a percentage of the total.

3. Methodology

This section further refines the studies under each task based on the methodology type, summarizes the core ideas of each theory, and reviews and evaluates the studies under each theory. Moreover, some potential solutions are expanded. According to the taxonomy based on task type and the taxonomy based on methodology type, the structure of this section can be summarized as shown in Fig. 4. It is important to note that open DG fault diagnosis, imbalance DG fault diagnosis, federated DG fault diagnosis are not subdivided due to the small number of studies on them or that they are not yet systematic, but they are still analyzed in detail in this section.

3.1. Multi-source DG fault diagnosis

In 2020, Zheng *et al.* [19] constructed a DG diagnostic method by describing each source domain as a point on the Grassmann manifold using local Fischer discriminant analysis. This is the first fault diagnosis study on multi-source DG and opens the prelude of DG fault diagnosis research. Compared to other tasks, the number of fault diagnosis studies on multi-source DG is overwhelming, and the methodological theories involved cover most of the theories mentioned in [1] and [2]. Therefore, we refer to [1] and [2] to further classify the fault diagnosis studies on multi-source DG, as shown in Fig. 5. Since studies on other DG tasks can all be considered as extensions of multi-source DG studies, most of them are grouped into the categories shown in Fig. 5. Specifically, existing DG studies can be categorized into three primary areas: data augmentation, domain alignment, and feature disentanglement. Additionally, emerging areas such as *meta*-learning and model interpretability are gaining traction. Note that most of the studies relate to more than one of these areas. This section will delineate how techniques from each area contribute to advancements in DG fault diagnosis, thereby assisting researchers in selecting and improving these techniques to develop effective diagnostic methods tailored to their specific needs.

3.1.1. Data augmentation

This area of techniques constructs a generative function $M(\cdot)$ to process the original samples x to obtain some augmented samples $x' = M(x)$, allowing both the number and diversity of available training samples to be improved. The learning objective of a data augmentation-based DG method is generally defined as:

$$\min_{H} \mathbb{E}_{x,y} \mathscr{L}_{\mathrm{CE}}(H(x), y) + \mathbb{E}_{x',y'} \mathscr{L}_{\mathrm{CE}}(H(x'), y') \tag{1}$$

where x' is an augmented sample, y' is its label, and $\mathscr{L}_{\mathrm{CE}}(\cdot,\cdot)$ is the cross-entropy loss. According to how the generative function is constructed, such techniques can be divided into three groups: **learning generative models**, **manipulating samples**, and **constructing physical simulation models**.

1) Learning generative models: learning generative models aims to expand the training samples by using generative models to generate latent domains. In existing literatures, the most used generative models are generative adversarial network (GAN) and its variants [45,46]. It should be noted that in previous GAN studies, it is generally only required that the generated samples are as similar as possible to the original samples to supplement the original samples. However, in the GAN-based DG fault diagnosis study shown in Fig. 6, the optimization objective of the generative model, in addition to maximizing the loss of the discriminator to make the generated samples have the same structural and semantic information as the original samples, is to maximize the distribution difference between the latent and source domains to simulate realistic distribution shift and to ensure the diversity of the latent domains. The optimization objective for GAN-based latent domain generation methods is generally defined as:

$$\min_{M} \max_{D} \mathbb{E}_x(\log(D(x))) + \mathbb{E}_x \log(1 - D(M(x))) - \mathbb{E}_x \mathscr{L}_{\mathrm{dis}}(M(x), x) \tag{2}$$

where $D(\cdot)$ is a discrimination function, and $\mathscr{L}_{\mathrm{dis}}(\cdot,\cdot)$ is a function that calculates the distribution distance between the augmented and original samples. After acquiring the latent domains, the feature extractor is expected to match not only the source domains but also the source and latent domains to further enhance the generalization of the captured features. In 2022, Zhuang *et al.* [47] improved the traditional GAN to generate diverse latent domains and used semantic consistent regularization to alleviate the semantic divergence between the source and latent domains, achieving health assessment of rotating machinery. In 2024, Wang *et al.* [48] designed an attack-defense strategy to enhance the generalization of diagnostic model, in which the model needs to distinguish generated attack samples from support samples to form a

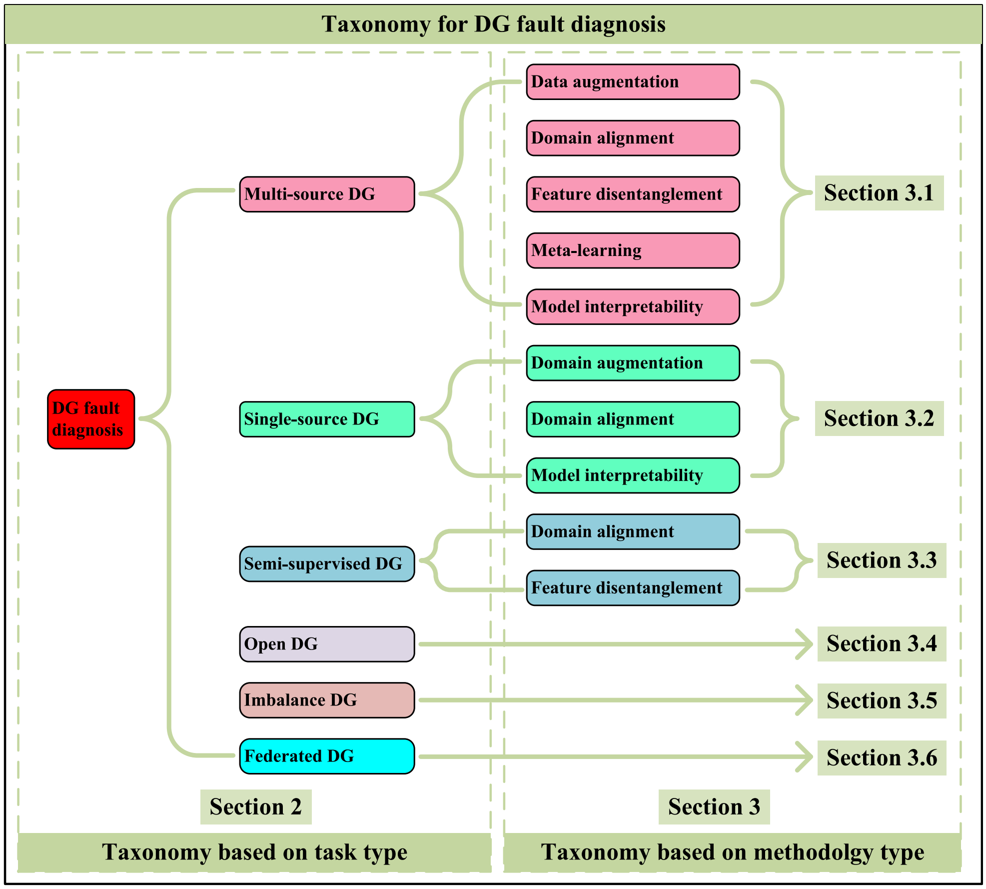

Fig. 4. Structure of the proposed taxonomy for DG fault diagnosis.

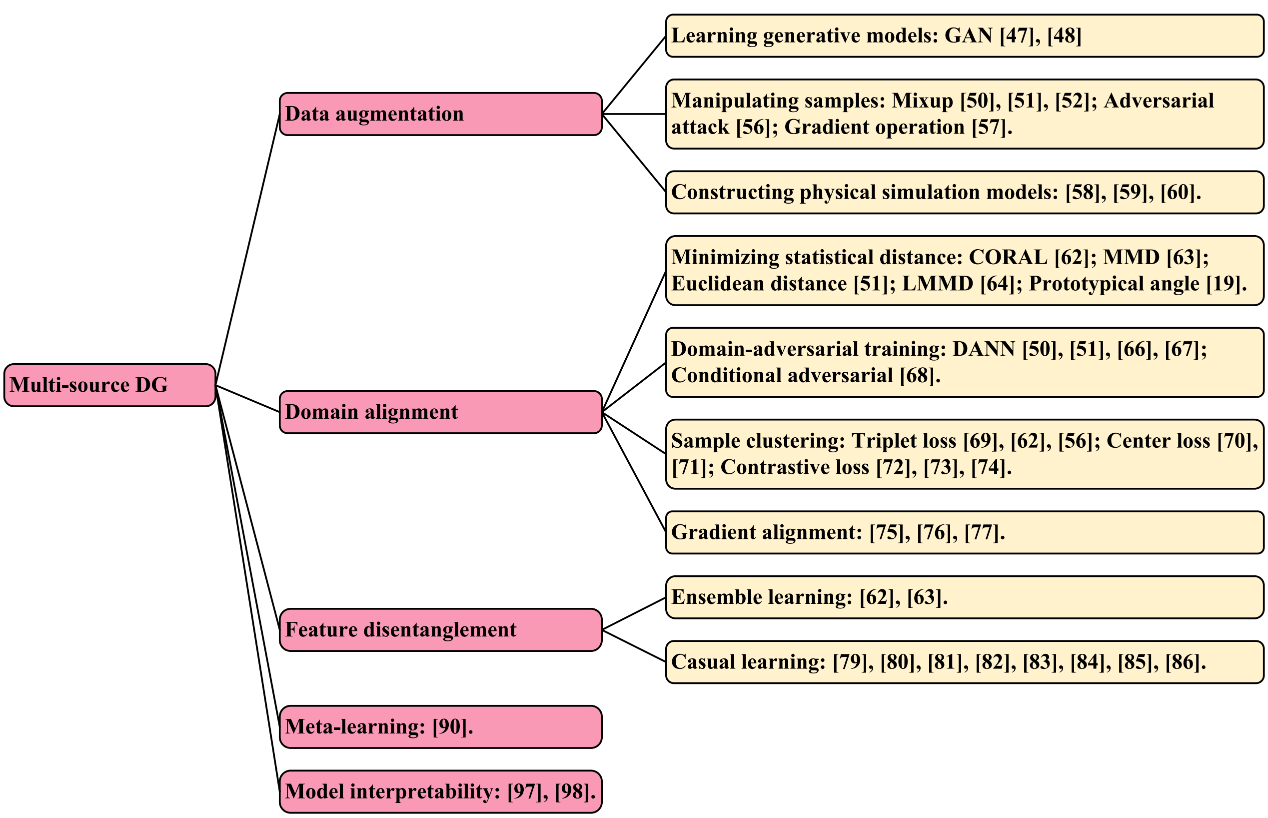

Fig. 5. Methodology type-based taxonomy for multi-source DG fault diagnosis.

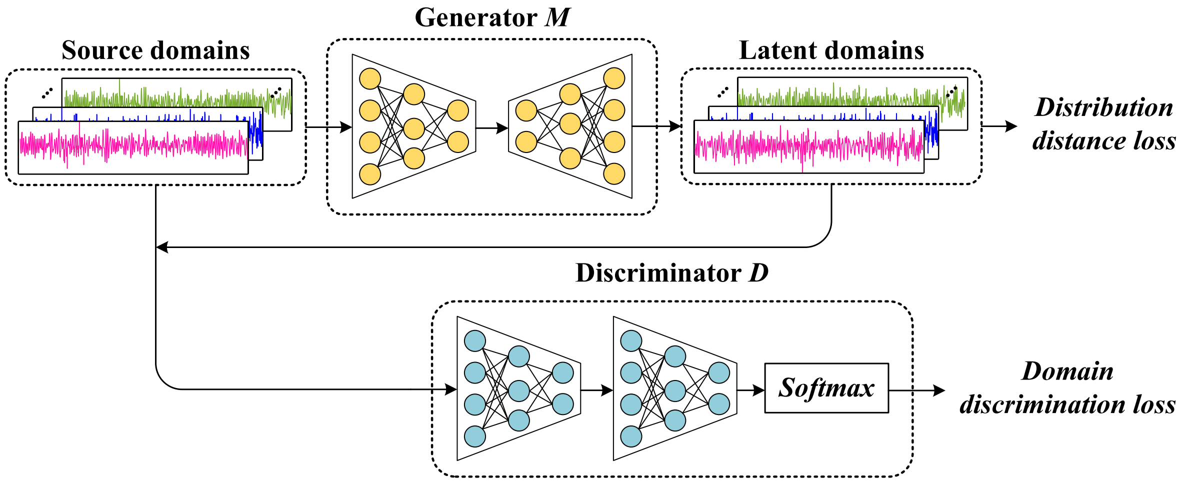

Fig. 6. GAN-based methods for generating latent domains [47], where distribution distance loss is $\mathbb{E}_x\mathscr{L}_{\text{dis}}(M(x), x)$, and domain discrimination loss is $\mathbb{E}_x(\log(D(x))) + \mathbb{E}_x\log(1 - D(M(x)))$.

new decision boundary that contains all unseen samples. Although constructing generative models yields diverse training samples, they tend to introduce adversarial training and thus present optimization challenges.

2) Manipulating samples: Manipulating samples is a relatively simple category of data augmentation methods compared to learning generative models. They obtain augmented samples by simply manipulating the original samples. The most popular manipulation method is Mixup [49], which generates an augmented sample-label pair by linearly combining two sample-label pairs in a random proportion. In the context of multi-source DG fault diagnosis, Mixup is typically improved to randomly mix sample-label pairs from multiple different domains while mixing their domain labels in the same proportion, which further enhances the diversity of generated samples. The difference between the original Mixup and the improved multi-domain Mixup is illustrated in Fig. 7, where the multi-domain Mixup can be defined as follows:

$$
\begin{aligned}
x' &= \sum_{k=1}^{K} \lambda^{(k)} x^{(k)} \\
y' &= \sum_{k=1}^{K} \lambda^{(k)} y^{(k)} \\
d' &= \sum_{k=1}^{K} \lambda^{(k)} d^{(k)}
\end{aligned}
\tag{3}
$$

where x' is the augmented sample, y' and d' are its label and domain label, respectively, $\lambda^{(k)}$ is a random variable drawn from a pre-defined Dirichlet distribution, and $d^{(k)}$ is the domain label of random sample $x^{(k)}$. This not only supplements the number and variety of source domains but also smooths the domain labels to better model optimization. The data augmentation methods used in [50,51], and [52] all follow the above idea, where [52] applies multi-domain Mixup to both the original samples and the representations of the samples.

There is also a manipulation known as adversarial attack, which produces attack samples by applying small perturbations to the original samples. These attack samples will try to disrupt the training direction of the model, which is trained with the goal of being able to defend against these attacks, thus improving its robustness. This type of method has received much attention in CV and typical methods such as FGSM [53], DeepFool [54], and JSMA [55] have been developed, however, their application in multi-source DG fault diagnosis is less. In 2021, Han *et al.* [56] generated adversarial samples by applying amplitude shift and Gaussian noise to the original samples, and trained the feature extractor to confuse the adversarial samples with the original samples to avoid overfitting when processing noisy samples.

In addition to the above manipulations, there exists another method to generate an augmented representation by manipulating the representation of a sample based on its gradients. In 2022, Tang *et al.* [57] proposed a representation gradient muting paradigm, which drops the dominant parts of the representation with high gradients, forcing the diagnostic model to focus on the remaining and label-relevant parts,

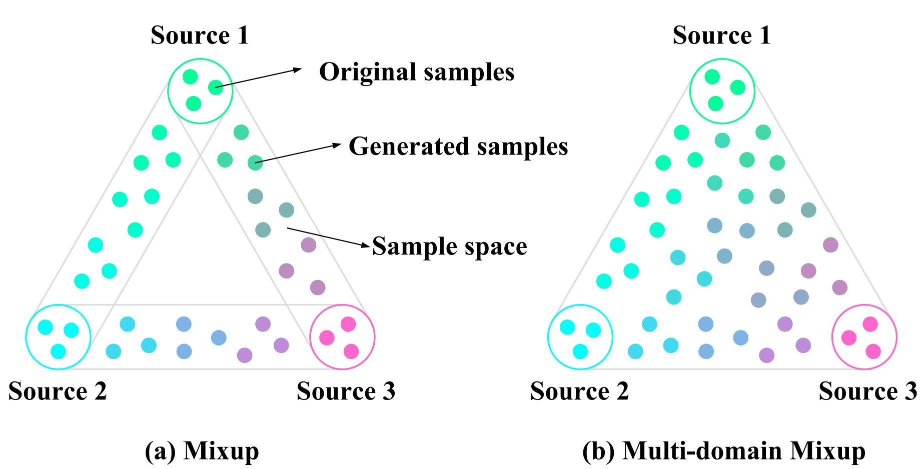

Fig. 7. Difference between Mixup and multi-domain Mixup.

thereby improving its generalization. This approach is similar to dropout, but differs in that it determines the parts of the representation that are dropped based on the gradients, whereas dropout drops them randomly.

3) Constructing physical simulation models: Compared with the previous two types of methods, the physical simulation model can generate a large number of samples even if the source-domain samples are not available. Existing physical simulation models are usually constructed by finite element analysis or numerical simulation, as shown in Fig. 8. The samples they generate are physically meaningful, which is difficult to achieve in the former methods. In addition, by adjusting the parameters of the simulation model, the generated samples can be controlled in terms of operating conditions and failure modes, which can flexibly meet the demands of various types of research and reduce the reliance on the simulation test bed. In 2024, Shi *et al.* [58] built a phenomenological model to generate simulation data with different modulation frequencies and signal-to-noise ratios, which provided support for subsequent diagnostic model training. In 2024, Gong *et al.* [59] constructed a dynamical simulation model to generate simulation data to capture the domain-invariant features under the condition that only a small amount of real data is available. In 2024, Pang *et al.* [60] designed a spectral background estimation algorithm to estimate the potential resonance frequencies in a real system, and used it to guide the parameterization of the physical simulation model, thus alleviating the overdependence of the parameter selection of the simulation model on experience. Although generating data from physical simulation models has many advantages over the previous two types of methods, it should be noted that the simulation model must reflect the real working conditions of the mechanical system, which requires the researchers to have sufficient prior physical knowledge. In addition, it is difficult for the simulation model to simulate the background noise in real working conditions, which may make the generated data too pure to provide strong support for model training.

3.1.2. Domain alignment

This area has been the focus of DG and has contributed notably to its success. The techniques in this area emphasize capturing domain-invariant features that can be generalized to unseen domains by matching the representation distributions of all available domains. The learning objective of a domain alignment-based DG method can be defined as:

$$\min_{H} \mathbb{E}_{x,y} \mathscr{L}_{\mathrm{CE}}(H(x), y) + \alpha \mathscr{L}_{\mathrm{Reg}} \tag{4}$$

where $\mathscr{L}_{\mathrm{Reg}}$ is a regularization term used to align all available domains, and α is a trade-off parameter. Based on the way the regularization term is constructed, we categorize such techniques into four groups, namely, **minimizing statistical distance**, **domain-adversarial training**, **sample clustering**, and **gradient alignment**.

1) Minimizing statistical distance: As shown in Fig. 9, minimizing statistical distance explicitly defines a distance to measure the difference between the representation distributions of any two domains, and the goal of model training is to minimize this difference while minimizing classification loss:

$$\min_{F,G} \mathbb{E}_{x,y} \mathscr{L}_{\mathrm{CE}}(G(F(x)), y) + \alpha \frac{2}{K \times (K-1)} \sum_{k \neq k'} \mathscr{L}_{\mathrm{dis}}(\mathscr{D}_k, \mathscr{D}_{k'}) \tag{5}$$

where $\mathscr{L}_{\mathrm{dis}}(\cdot, \cdot)$ is a function that calculates the distance between the representation distributions of any two domains. The most widely used distances are maximum mean discrepancy (MMD), followed by correlation alignment (CORAL). In addition, a variant of MMD, local MMD (LMMD) [61], is also highly popular. They do not require the use of class information of the samples and thus were initially applied to DA to measure the difference between the source and target domains, where the target-domain samples are unlabeled. In practice, MMD and CORAL compute the difference between two domains at a global level and can therefore only be used to align the domains globally. In contrast, LMMD is concerned with the differences between the relevant subdomains (set of samples with the same label) of two domains, and therefore can be used to align the domains at a class level. In 2022, Zhao *et al.* [62] proposed a DG diagnostic method that combines domain invariance and domain specificity, which uses CORAL for global distribution alignment. In 2023, Wang *et al.* [63] constructed a DG fault diagnosis model with multiple domain-specific classifiers, and the inter-domain alignment strategy it employs is based on MMD. Note that even though [62] and [63] belong to the feature disentanglement methods as a whole, they still use the domain alignment methods when extracting domain-invariant features. In 2024, Fan *et al.* [51] developed a deep mixed DG network for fault diagnosis, which fuses all available domains by minimizing the Euclidean distance between representations of different domains. In 2022, Hu *et al.* [64] designed a deep subdomain generalization network based on LMMD for the health monitoring of high-speed train

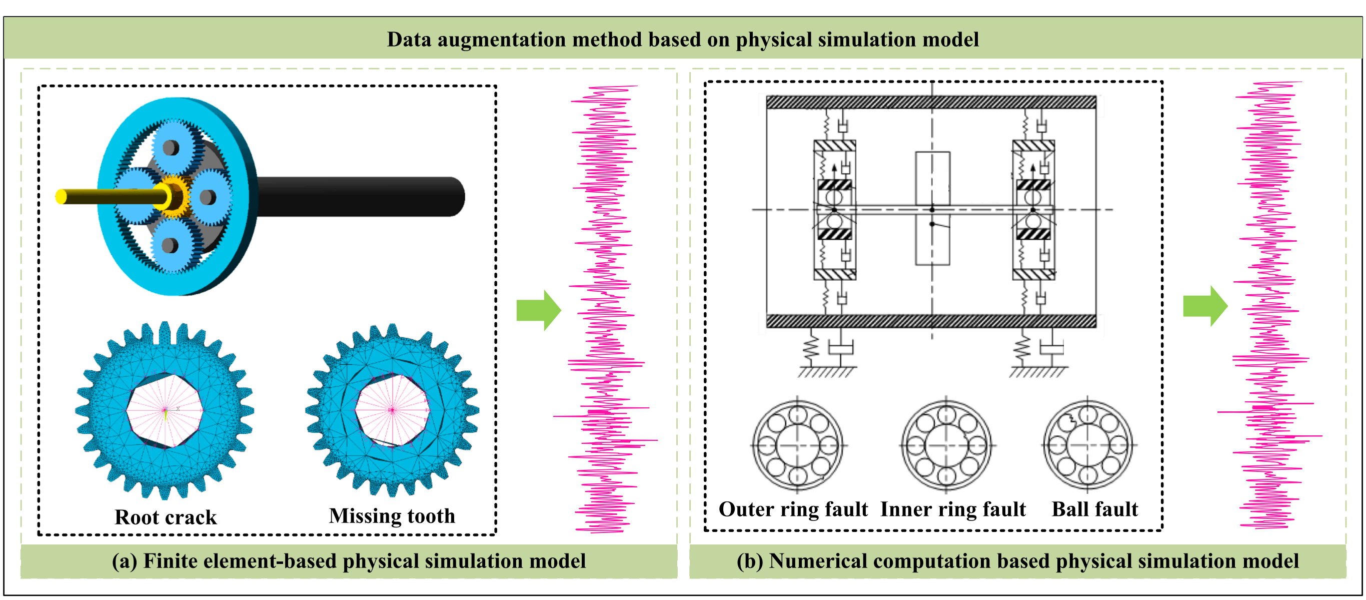

Fig. 8. Data augmentation methods based on physical simulation model.

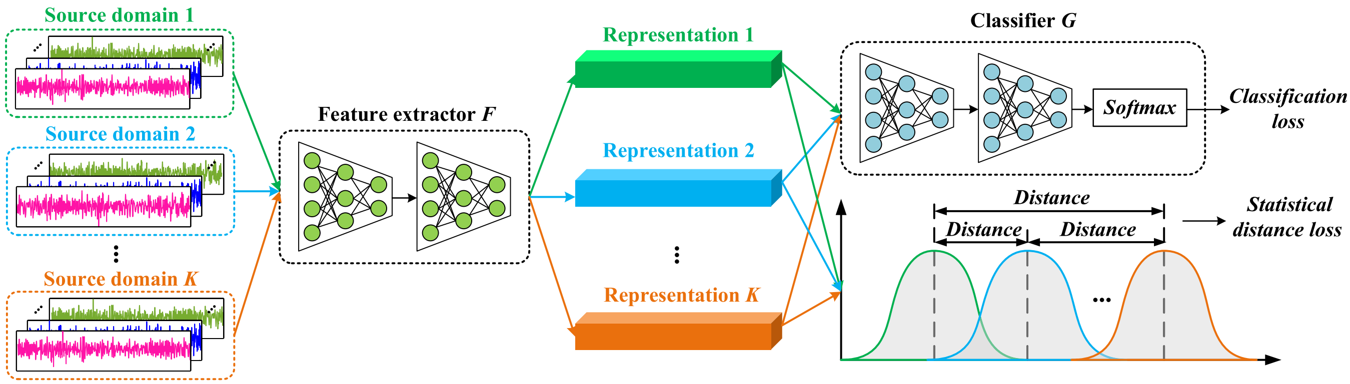

Fig. 9. Domain alignment methods based on maximizing statistical distance [63], where classification loss is $\mathbb{E}_{x,y}\mathscr{L}_{\mathrm{CE}}(G(F(x)),y)$, and statistical distance loss is $2\sum_{k\neq k'}\mathscr{L}_{\mathrm{dis}}(\mathscr{D}_k,\mathscr{D}_{k'})/K\times(K-1)$.

brake pads, allowing the subdomains with the same label to find an appropriate common subspace. [19] found the average subspace of all domains by minimizing the sum of the distances of all domains to a certain subspace, where the distance between two subspaces is computed using the prototypical angle. Overall, minimizing statistical distance belongs to a category of methods that are relatively straightforward to implement.

2) Domain-adversarial training: Domain-adversarial training does not pre-define a distance to measure the difference between two domains, but instead uses a domain discriminator to determine whether they are confused. Specifically, feature extractor and domain discriminator play a min–max two-player game, where the former makes the representations of all source domains as domain agnostic as possible, while the latter tries to determine from which domain these representations originate. As shown in Fig. 10, the domain discriminator can be similar to the classic domain-adversarial neural network (DANN) [27] with only one module, which does not utilize class information and thus confuses domains at the global level. At this point, the optimization objective of the model is as follows:

$$\max_{D}\min_{F,G}\mathbb{E}_{x,y}\mathscr{L}_{\mathrm{CE}}(G(F(x)),y)-\alpha\mathbb{E}_{x,d}\mathscr{L}_{\mathrm{CE}}(D(F(x)),d) \tag{6}$$

where d is the domain label of sample x. Alternatively, the domain discriminator can consist of multiple modules as shown in Fig. 11, each targeting a fault class, thus confusing domains at the class level. This is also known as conditional adversarial training [65], whose optimization objective is as follows:

$$\max_{D_0,D_1,\ldots,D_{C-1}}\min_{F,G}\mathbb{E}_{x,y}\mathscr{L}_{\mathrm{CE}}(G(F(x)),y)-\alpha\frac{1}{C-1}\sum_{c=0}^{C-1}\mathbb{E}_{x_c,d_c}\mathscr{L}_{\mathrm{CE}}(D_c(F(x_c)),d_c) \tag{7}$$

where x_c is a sample with class c, d_c is its domain label, and $D_c(\cdot)$ is a discrimination function for class c. The domain-adversarial diagnostic models proposed in [50,51,66], and [67] are all globally aligning the source domains, where [50] and [67] also reduce the risk of negative transfer by adaptively weighting the source domains. In contrast, Zhang *et al.* [68] proposed a conditional adversarial DG diagnostic model in 2022, aligning the source domains at the class level. Moreover, [68] designed a new adversarial strategy so that the model can achieve conditional adversarial purpose using a discriminator with only a single module, significantly reducing the training cost. Compared to minimizing statistical distance, domain-adversarial training provides more flexibility in measuring distribution differences but is also more difficult to optimize.

3) Sample clustering: Sample clustering does not focus on the difference in representation distribution between two domains or two subdomains as the previous two categories do, but explicitly requires that representations of the same class from all domains are clustered, while representations of different classes are separated from each other. As a result, samples of the same class in different domains are projected to a common subspace thus achieving class-level domain alignment. This category of methods takes full advantage of the fact that the labels of the samples in the aligned domains are available in multi-source DG, which is usually neglected in the previous two categories. In practice, such methods usually involve triplet loss and center loss, whose operating principle is shown in Fig. 12. In 2024, Shen *et al.* [69] developed a novel triplet loss-based DG network for bearing fault diagnosis. [62] used a combination of CORAL and triplet loss to align source domains at both the global and class levels. [56] learned a generalizable discriminant structure from the source domains using only triplet loss. In 2023, Wang *et al.* [70] designed an adaptive class center generalization network for bearing fault diagnosis, in which the centers in center loss can be adaptively updated. In 2024, Jia *et al.* [71] proposed a dynamically

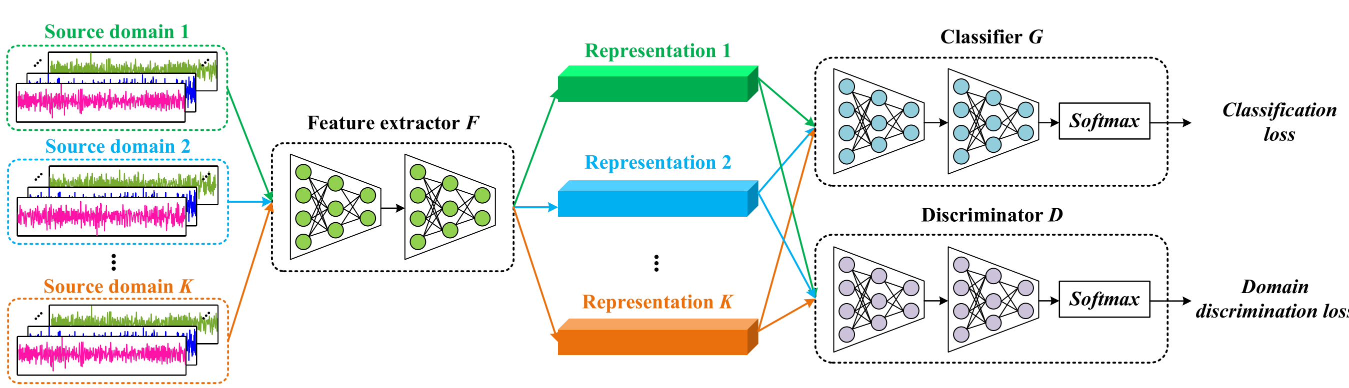

Fig. 10. Domain alignment methods based on DANN [67], where classification loss is $\mathbb{E}_{x,y}\mathscr{L}_{\mathrm{CE}}(G(F(x)),y)$, and domain discrimination loss is $\mathbb{E}_{x,d}\mathscr{L}_{\mathrm{CE}}(D(F(x)),d)$.

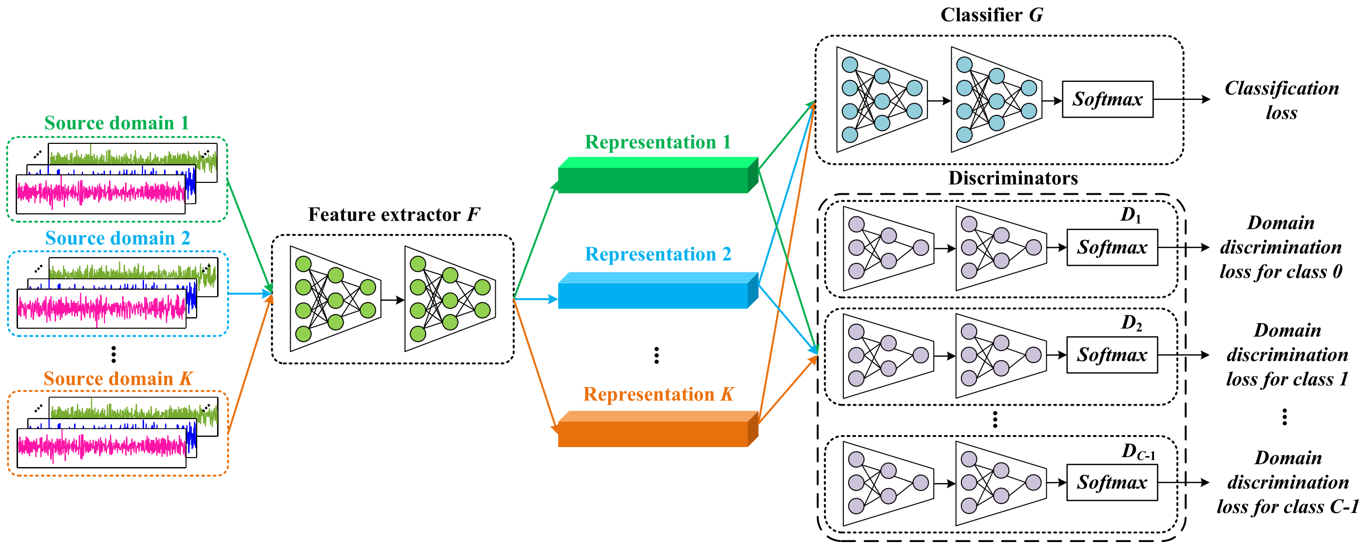

Fig. 11. Domain alignment methods based on conditional domain-adversarial networks [65], where classification loss is $\mathbb{E}_{x,y}\mathscr{L}_{\mathrm{CE}}(G(F(x)),y)$, and domain discrimination loss for class c is $\mathbb{E}_{x_c,d_c}\mathscr{L}_{\mathrm{CE}}(D_c(F(x_c)),d_c)$.

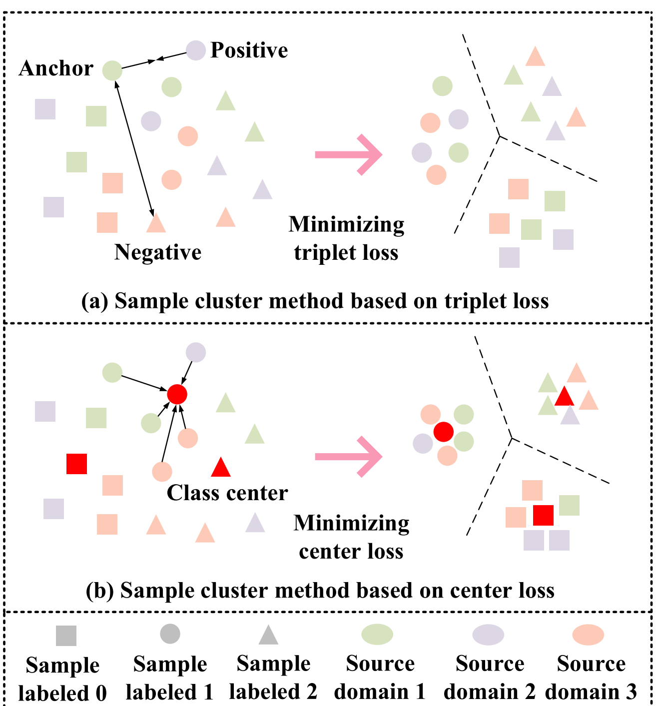

Fig. 12. Operating principle of sample clustering methods.

balanced dual prototypical DG network for cross-machine fault diagnosis. [71] is not only similar to center loss searching for class centers, but also searches for domain centers to compensate for the defect of the sample clustering methods, which is only able to learn domain-invariant features but is difficult to suppress domain-specific features.

Contrastive learning is also commonly used to develop sample clustering methods. In 2022, Ragab *et al.* [72] proposed a conditional contrastive DG method for fault diagnosis, where mutual information of the same classes in different domains is maximized while mutual information of different classes is minimized. In 2023, Shi *et al.* [73] developed a DG network for cross-machine fault diagnosis based on contrastive loss. [73] treats two samples of the same class from two separate domains as a positive pair and two samples of different classes as a negative pair. In contrast, [56,62], and [72] find anchor, positive, and negative samples to construct a triple based only on the class of the samples, regardless of the domain they are from. The difference between [73] and other methods in constructing sample groups necessitates the use of domain labels in [73] while other methods do not. In 2024, He *et al.* [74] developed a DG method based on time–frequency self-contrastive learning for the diagnosis of compound faults in industrial motors. Significantly different from the aforementioned sample clustering methods, [74] utilizes signal processing techniques to obtain time-domain features and frequency-domain features of a sample to construct self-contrast pairs. Therefore, it does not rely on sample labels or domain labels, nor does it require samples from multiple domains.

4) Gradient alignment: Gradient alignment methods capture domain-invariant features by normalizing the optimal optimization direction of the model over each source domain to find a suitable common direction. In 2024, Ren *et al.* [75] proposed a *meta*-learning framework for gradient alignment, where *meta*-learning was used to circumvent the problem of unsolvable higher-order derivatives when computing the inner product of gradients. In 2024, Ma *et al.* [76] developed a sharpness-aware gradient alignment method for DG fault diagnosis under conditions where labels contain noise. The method learns domain invariance by coordinating the gradients to create a flat region on the loss map with low loss values, and further finding a flat minimum on this region. In 2023, Ma *et al.* [77] devised a gradient aligned DG diagnostic method based on a mutual teaching teacher-student network, which utilizes fine-grained gradient alignment to emphasize higher-order domain invariance and further collaborates with lower-order distributional statistics to ensure robust gradient alignment.

3.1.3. Feature disentanglement

The difference between this area and domain alignment is that it focuses not only on domain-invariant features, but also on domain-specific features. Therefore, this area of techniques usually requires a decomposition of a feature into the above two sub-features to be handled separately. Based on the mechanism of implementing feature disentanglement, we categorize such techniques into two groups, namely, **ensemble learning**, and **causal learning**.

1) Ensemble learning: Ensemble learning is widely used to improve model performance. As shown in Fig. 13, DG typically constructs an ensemble model that consists of a domain-shared feature extractor and multiple domain-specific classifiers, where the extractor addresses domain-invariant features and each classifier addresses domain-specific

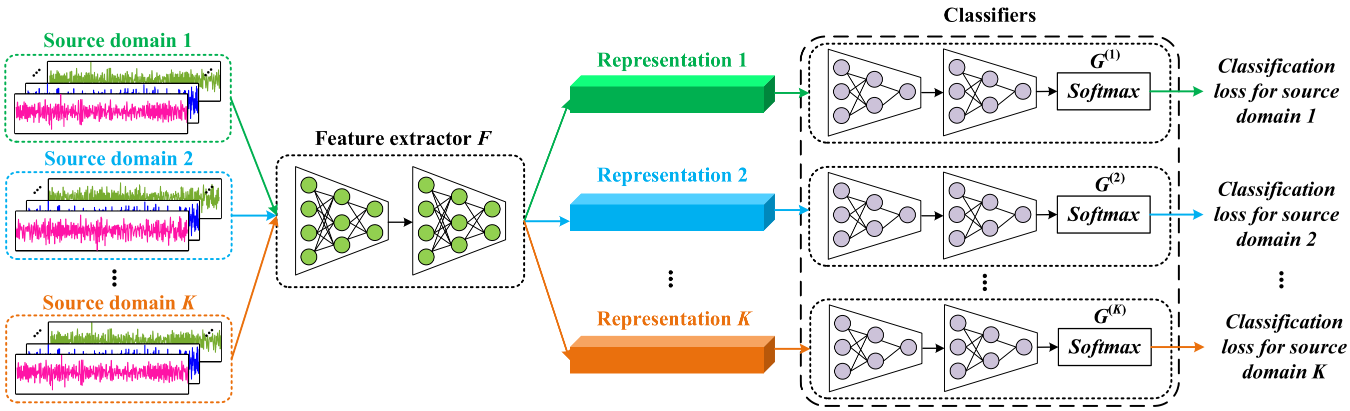

Fig. 13. Feature disentanglement method based on ensemble learning [62], where classification loss for source domain k is $\mathbb{E}_{x^{(k)},y^{(k)}}\mathscr{L}_{\mathrm{CE}}(G^{(k)}(F(x^{(k)})),y^{(k)})$.

features of the corresponding domain. The optimization objective of the ensemble model can be defined as:

$$\min_{F,G^{(1)},G^{(2)},\ldots,G^{(K)}}\frac{1}{K}\sum_{k=1}^{K}\mathbb{E}_{x^{(k)},y^{(k)}}\mathscr{L}_{\mathrm{CE}}(G^{(k)}(F(x^{(k)})),y^{(k)}) \tag{8}$$

where $G^{(k)}(\cdot)$ is a classification function for the source domain k. Such methods are generally highly correlated with the domain alignment methods. [62] used multiple domain-specific classifiers to retain domain-specific features in addition to CORAL and triplet loss for domain alignment, and the final diagnostic results are determined collaboratively by these classifiers. [63] first learned the domain-specific features through multiple domain-specific classifiers, and then used these classifiers to direct the domain-shared feature extractor to remove these features. Also, MMD was employed to further guide the extractor to capture domain-invariant features. Note that although both [62] and [63] use multiple classifiers to extract domain-specific features, [62] retains them and utilizes the voting mechanism to use them for decision-making, while [63] discards them for the further purification of domain-invariant features.

2) *Casual learning*: Casual learning assumes data contains casual information and non-casual information, where casual information is label-related and invariant, while non-causal information is label-independent and domain-specific [78]. As shown in Fig. 14, causal learning usually starts with the construction of a structural causal model that describes the data generation process based on the relationship between different variables (noise, load, speed, machine, etc.). The fitness of the structural causal model for the task at hand determines the

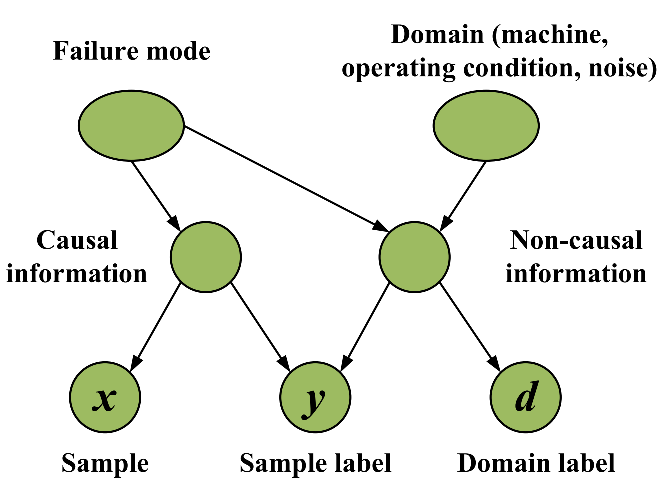

Fig. 14. Structural causal model for casual learning-based DG fault diagnosis [81].

performance of causal learning. In addition, since causal and non-causal features are usually difficult to be observed and formalized, it requires to speculate the properties that causal features should satisfy. Also, objective functions should be constructed based on these speculations to impose invariant regularization on causal features thus reconstructing the causal mechanism. In 2022, Li *et al.* [79] made the first attempt to introduce causal learning to DG fault diagnosis, which considers environmental noise as background and features caused by speed, and load as domain-specific features. In [79], layer normalization was used to regularize noisy background and instance normalization was used to remove domain-specific features. In addition, a causal loss was designed to extract invariant features. In 2023, Guo *et al.* [80] proposed a causal explaining guided DG model that not only enhances the generalization of the model by directing it to focus on causal features, but also puts humans in the decision loop of diagnosis through post-hoc explaining. In 2024, Jia *et al.* [81] developed a causal decoupling DG method for time-series signals, in which causal aggregation loss was used to separate causal and non-causal information in fault features, supplemented by reconstruction loss to ensure the completeness of the separated information.

Causal learning is also commonly used for cross-machine fault diagnosis. In 2023, Jia *et al.* [82] designed a deep causal factorization network to separate the cross-machine causal features and the non-causal features, where the former maximizes the entropy of the predicted outputs of the domain discriminator, while the latter maximizes the entropy of the classifier. In 2023, Li *et al.* [83] developed a causal disentanglement network for cross-machine knowledge generalization and diagnosis of continuous degradation patterns in bearings, rather than being limited to fixed-level fault modes as is commonly done. In 2023, Li *et al.* [84] proposed a causal consistency network for multi-machine collaborative DG fault diagnosis. The question of whether causal representations should be subjected to invariant regularization in fault diagnosis, as is usually the case, is explored for the first time. In 2024, Cheng *et al.* [85] proposed a learning rule called object-conditional domain invariant to enable causal learning, which accomplished bearing DG fault diagnosis under the condition that the source-domain data is a mixture of data from various operating conditions and machines with domain labels inaccessible. In 2024, Zhu *et al.* [86] designed a causal and physical co-driven DG network. It realizes domain-invariant feature extraction and domain-specific knowledge embedding by exploiting prior physical knowledge of unknown target machines while mining fault causality.

3.1.4. Meta-learning

Meta-learning, also known as learn to learn, aims to learn from episodes sampled from multiple related tasks for future learning [87,88], and it has been applied to DG. Meta-learning-based DG methods do not explicitly require the model to learn certain representations for knowledge generalization, but rather expose the model to multiple domain-shift tasks and learn on these tasks to abstract knowledge that can be used to learn on unseen domain-shift tasks. Typically, the available source domains are randomly divided into *meta*-train domains and *meta*-test domains, and the *meta*-optimization goal is that the model trained on the *meta*-train domains can be generalized well to the *meta*-test domains [89]. Meta-learning has been favored by scholars in the field of CV as a promising approach for solving DG problems, but relatively little research has been conducted in multi-source DG fault diagnosis. In 2022, Wang *et al.* [90] designed a model-agnostic learning procedure for DG diagnostic model, which finds invariant gradient directions across domains by maximizing the dot product between the gradients of the source domains.

3.1.5. Model interpretability

Model interpretability has become a promising research direction in fault diagnosis [91–96]. Existing research on interpretable fault diagnosis can be categorized into ante-hoc explaining, which develops interpretable modules embedded in deep model to give physical meaning to the diagnostic results, and post-hoc explaining, which uses the results as a basis to infer the logic of the model in making decisions. Since the ante-hoc explaining methods assume that the generalization of a model can be enhanced when it is embedded with physical knowledge, it fits well with multi-source DG fault diagnosis. Meanwhile, it is also important to utilize post-hoc explaining methods to help humans understand DG diagnostic models and to establish the dependency relationship between humans and models. In 2022, Liu *et al.* [97] designed an interpretable convolutional neural network based on the Morlet wavelet transformation and proved the invariance of its extracted scattering features for linear time-invariant systems, showing that the model can perform DG fault diagnosis across different signal transmission paths. In 2024, Zhu *et al.* [98] proposed a decoupled interpretable robust DG network for cross-domain fault diagnosis from artificial data to real data, in which a neural basis function decoupling module was used to decompose the signal into fault-related and fault-irrelevant basis functions, supplemented by a pruning network to remove the latter.

3.2. Single-source DG fault diagnosis

Existing single-source DG fault diagnosis studies mainly cover the areas of data augmentation, domain alignment, and model interpretability, as shown in Fig. 15.

Since a single source domain provides less knowledge, it is necessary to use the methods of learning generative models to generate latent domains. Following this, the feature extractor needs to be able to match the source and latent domains to improve the robustness. This paradigm of combining data augmentation and domain alignment, with a generator and a feature extractor performing adversarial training, has been favored by scholars, as shown in Fig. 16. Its optimization objective is defined as:

$$\begin{gathered}\min_{F,G}\mathbb{E}_x\mathscr{L}_{\mathrm{CE}}(G(F(M(x))),y')+\mathbb{E}_x\mathscr{L}_{\mathrm{CE}}(G(F(x)),y)+\mathbb{E}_x\mathscr{L}_{\mathrm{dis}}(F(M(x)),F(x))\\ \max_{M}\mathbb{E}_x\mathscr{L}_{\mathrm{dis}}(F(M(x)),F(x))\end{gathered} \tag{9}$$

where y' is the label of the augmented sample $x' = M(x)$, and $\mathscr{L}_{\mathrm{dis}}(\cdot,\cdot)$ is a function that calculates the distance between the augmented sample x' and the original sample x. In 2023, Zhao *et al.* [21] proposed an adversarial mutual information-guided network for single-source DG fault diagnosis. In [21], the generator generates diverse samples by minimizing the mutual information between the generated samples and the source-domain samples. Meanwhile, the feature extractor utilizes contrastive loss to achieve class-level domain alignment by maximizing the mutual information between them. In 2024, Wang *et al.* [99] designed a multi-scale style generative and adversarial contrastive model with a similar operation mechanism as [21]. Its improvement over [21] is that it designs the generator as a multi-branch network based on style learning. In 2023, Jiang *et al.* [100] designed a VIT-based conditional adversarial DG network for chiller fault diagnosis, in which a cooperative conditional domain discrimination strategy was used to enhance the model's ability to discriminate the distributions of the extracted features, thus aligning their conditional distributions. In 2024, Pu *et al.* [101] proposed a single-source incremental generalization network characterized by iteratively generating latent domains in an incremental manner. In addition, the method maximizes the InfoNCE loss between the source and latent domains to ensure that the latent domains are distinct from the source domains, while maintaining the semantic consistency of the latent domains with the source domains through the cyclic consistency loss. It is worth noting that in the previously mentioned generative model-based studies [47,48], the generative model and the diagnostic model are separated, and the adversarial training is conducted with the generator and the domain discriminator in GAN. However, in [21,99], and [101], the generative model and the diagnostic model are integrated as shown in Fig. 16, where the feature extractor of the diagnostic model acts as the discriminator of the previous GAN. Therefore, it is the generator and the feature extractor that are used for adversarial training.

In multi-source DG, samples from multiple domains and their domain labels can be linearly combined using Mixup to generate samples with new domain labels. However, in single-source DG, where only one source domain is available, synthesizing latent-domain samples via Mixup is a challenging problem. In 2024, Tang *et al.* [102] proposed a HmmSeNet model for single-source DG, where Mixup is used to combine the original samples with the samples generated by histogram matching to obtain new samples. These samples have the same semantics as the source-domain samples but are distributed differently from them.

In addition to employing data augmentation, embedding prior physical knowledge to the model can also alleviate the problem of insufficient information in a single source domain. In 2024, Kim *et al.* [103] proposed a single DG and physically interpretable framework for bearing fault diagnosis, which utilizes signal preprocessing to embed the

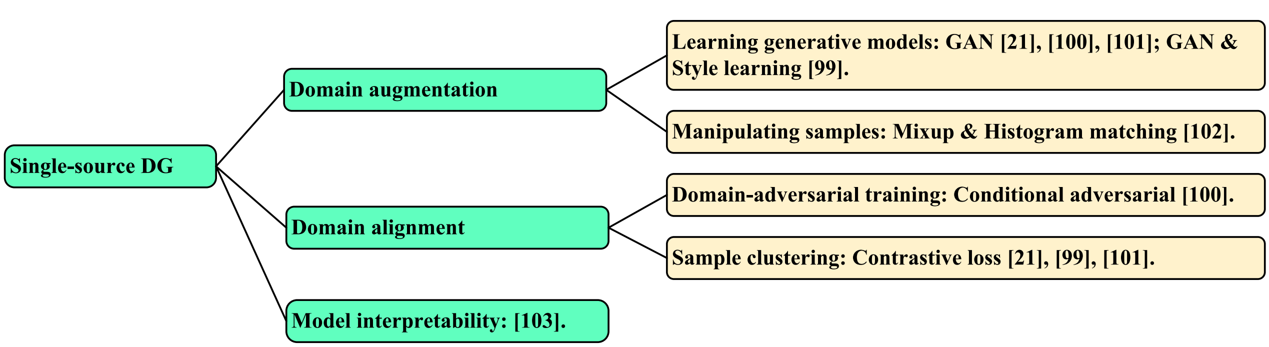

Fig. 15. Methodology type-based taxonomy for single-source DG fault diagnosis studies.

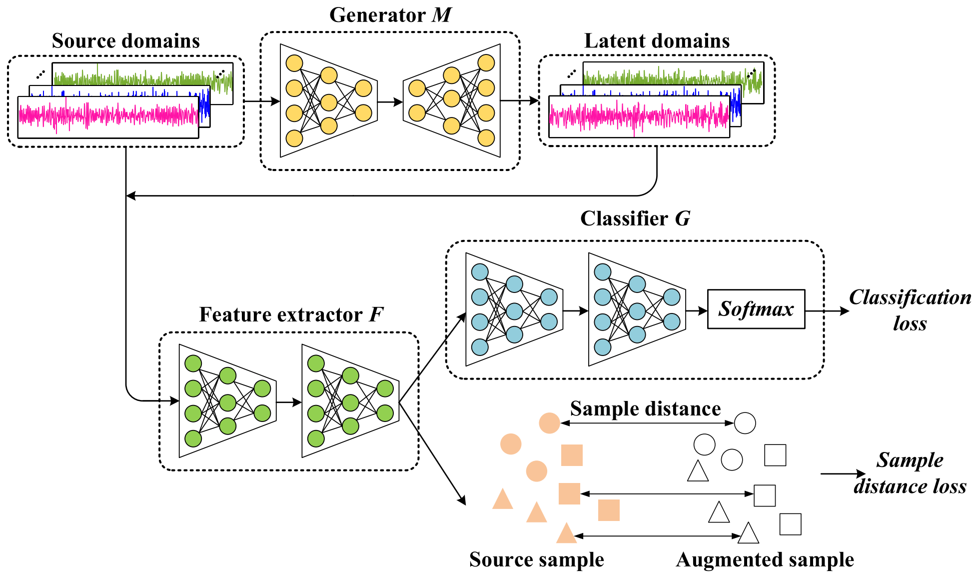

Fig. 16. Adversarial single domain DG network based on data augmentation [21], where classification loss is $\mathbb{E}_x \mathscr{L}_{\mathrm{CE}}(G(F(M(x))), y') + \mathbb{E}_x \mathscr{L}_{\mathrm{CE}}(G(F(x)), y)$, and sample distance loss is $\mathbb{E}_x \mathscr{L}_{\mathrm{dis}}(F(M(x)), F(x))$.

prior knowledge that the fault features in bearing signals are impulse signals with characteristic fault order into the diagnostic model, thus improving its generalization.

Overall, research on single-source DG for fault diagnosis remains relatively scarce. The primary challenge in this area is compensating for the limited information available from a single source domain. Constructing a generative model embedded with physical knowledge seems to be a promising solution. In addition, the methods used for multi-source DG that do not explicitly require the use of domain labels can also serve as potential solutions for single-source DG.

3.3. Semi-supervised DG fault diagnosis

As shown in Fig. 17, existing semi-supervised DG fault diagnosis studies have focused on how to align labeled source domain and unlabeled source domains, which is similar to DA that asks to align labeled source domain and unlabeled target domain. The key difference between the two is that the target domain in the former is an unseen new domain, whereas the target domain in the latter participates in training. Despite the difference, since both methods aim to identify domain-invariant features that should be generalized across varied domains, the techniques used in semi-supervised DG and DA can often be adapted from one to the other. Regardless of DA or semi-supervised DG, a further requirement to align domains at the class level often requires pseudo-labeling the unlabeled samples using knowledge from the labeled samples, thereby complementing the missing class information in the unlabeled domain(s). In addition to domain alignment, there are a few semi-supervised DG fault diagnosis methods that apply feature disentanglement.

In 2020, Liao *et al.* [104] designed a deep semi-supervised DG fault diagnostic model based on Wasserstein GAN with gradient penalty and pseudo-label learning. In 2022, Li *et al.* [105] proposed an adversarial DG network for bearing fault diagnosis, in which the domain discriminator consists of two classifiers, and their decision differences are used to characterize the similarity between the representations of different domains. In 2023, Ren *et al.* [106] developed a deep fuzzy generalization network that utilizes adversarial training to implement global domain alignment and pseudo label-based center loss to enable class-level domain alignment. In 2023, Ren *et al.* [107] used two network branches to extract discriminative and domain-invariant features, respectively, and fused them via a fusion module.

In addition to the above domain alignment methods, there are some semi-supervised DG fault diagnosis studies applying feature disentanglement methods. In 2023, Zhao *et al.* [108] proposed a multi-assistance semi-supervised DG network in which the domain alignment method is only used to assign pseudo-labels to unlabeled samples, and low-order decomposition is used to guide the training of domain-specific classifiers and domain-invariant classifier in the main branch. In 2024, Song *et al.* [109] proposed a contrast-assisted domain-specificity removal network, which utilizes the domain discriminator to guide the domain-specific feature extractor to learn information about domain classification. Meanwhile, it further makes the extractor conduct adversarial training with the fault classifier to ensure that the features it learns are independent of the fault categories. It is worth mentioning that [109] utilizes the domain-specific feature extractor to capture domain-specific features, which is different from existing studies that mostly use domain-specific classifiers to achieve this goal.

Conducting semi-supervised DG fault diagnosis tasks fully leverages

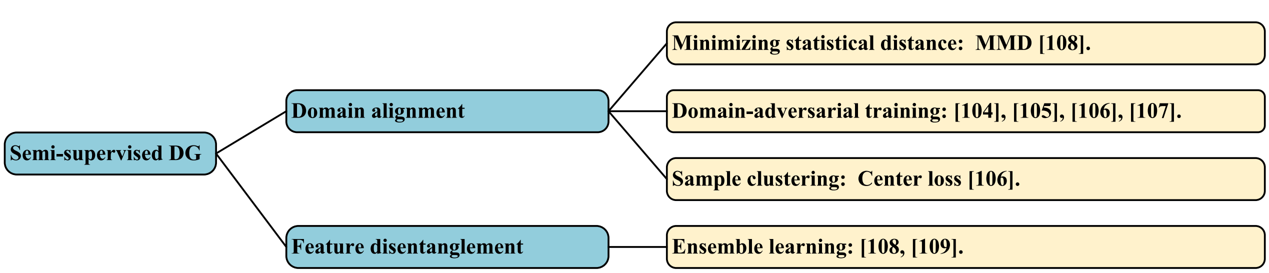

Fig. 17. Methodology type-based taxonomy for semi-supervised DG fault diagnosis studies.

a large amount of unlabeled data, thereby saving the cost of labeling. It not only generalizes the model to unseen target domains but also enables the model to handle data from unlabeled domains like DA models. In particular, a typical DA model can only be used for one unlabeled domain, whereas a semi-supervised DG model can handle multiple unlabeled domains simultaneously. To develop a high-performance semi-supervised DG model, one key aspect is how to assign high-quality pseudo-labels to unlabeled samples. In addition, further consideration could be given to how to align labeled and unlabeled domains when they do not share the same label set.

3.4. Open DG fault diagnosis

Existing open DG fault diagnosis studies [110,111,20] do not fully follow the setting of open DG described in Section 2. They only consider the presence of samples with unknown fault classes in the target domain, ignoring the setting that the source domains do not share the same label set. In addition, we note that in the open DG task setting for [110], there are private classes in source domains that are not present in target domains. This is practically meaningless, since the target domains are only used as the test sets in DG and do not participate in training as DA does.

The task of detecting samples from unknown classes in the target domain is similar to the topic of out-of-distribution (OOD) detection [112–114] which aims to reject unseen OOD samples only by learning knowledge from in-distribution samples. Therefore, some OOD detection methods such as uncertainty-based methods, reconstruction-based methods, and softmax output-based methods can be readily applied to open DG. In 2022, Ge *et al.* [111] proposed an adaptive fault diagnosis method that not only detects samples of new classes in the target domain but also further categorizes the new fault classes through K-means algorithm. In 2022, Zhao *et al.* [20] designed an adaptive open set DG network to learn the optimal decision boundary for each known class, which encompasses samples from the corresponding class and rejects samples from unknown classes.

The studies mentioned previously do not address how models can be generalized to unseen domains in the open DG fault diagnosis task described in Section 2. Here, we give some potential solutions. Due to severe class mismatches between source domains, differences in their global distributions are inherent, making them difficult to align at the global level. Therefore, we recommend developing sample clustering methods to align source domains directly at the class level. In addition, *meta*-learning that does not explicitly require the learning of domain-invariant representations is also a promising approach. Furthermore, given the challenges associated with aligning source domains, another viable strategy might be to employ an ensemble model that focuses on learning domain-specific features. The final diagnostic decisions are made collaboratively by all ensemble members [17,115,116]. In addition to using the above representation learning methods, it is also possible to utilize data augmentation methods such as Mixup and CutMix [117] to supplement the missing classes in source domains. These methods can generate new labels by linearly combining the original labels, so that the new labels are likely to be the missing labels.

3.5. Imbalance DG fault diagnosis

The problem of DA fault diagnosis under class imbalance has been widely studied [118–121], but the more challenging and practical problem of imbalance DG fault diagnosis has not been emphasized. At present, only one diagnostic method for imbalanced DG has been reported. In 2024, Zhao *et al.* [122] proposed a semantic-discriminative augmentation-driven network in which Mixup with semantic regularization is used to compensate for minority classes. Unlike other existing Mixup-based methods, [122] only linearly combines samples from the same class to directionally generate samples from that class. Subsequently, [122] further maintains semantic information of the generated samples by reducing the distribution difference between them and the original samples. In addition to utilizing data augmentation methods, other methods that have been applied to the class imbalance problem can also serve as potential solutions for imbalance DG. For example, the loss function can be improved to increase the penalty for the model misclassifying the minority classes of samples, increasing its sensitivity to them.

3.6. Federated DG fault diagnosis

In Federated DG fault diagnosis, each client can only access its own private data, excluding the data of other domains held by other clients. As a result, the aforementioned methods that directly measure the difference in representation distributions across domains or the distance of samples from the same class are difficult to apply. Moreover, we note that in [123], the client sends the representations learned in local training to the central server, which computes the distribution differences between the representations. This is actually prohibited because representations contain high-dimensional information about the data, and uploading representations can also cause privacy leakage.

In order to achieve domain alignment in a privacy-preserving manner, an alternative approach is to construct a reference distribution and make the distributions of the representations learned by all clients close to this reference distribution, as shown in Fig. 18. In 2022, Wang *et al.* [124] proposed a federated adversarial DG network in which the reference distribution is generated by generator trained collaboratively by clients. The reference distribution generated by the local generator will approximate the local representation distribution, and the global generator aggregated by these local generators can generate a reference distribution centered on multiple clients for guiding domain alignment. In 2024, Li *et al.* [125] proposed a privacy-preserving federated DG fault diagnosis method incorporating consensus knowledge, whose generator in the cloud inversely maps labels as inputs to obtain a reference representation distribution, transforming the centralized distribution alignment problem into a two-by-two distribution alignment problem. In 2024, Zhao *et al.* [126] developed a federated distillation DG framework in which the generator can learn the distribution of local data. Unlike the generators in previous studies that generate a reference distribution to guide the domain alignment training, it directly generates fake data to assist the other clients. And, these clients will align the local data and fake data to capture the domain-invariant features by using a low-rank decomposition method.

In addition, as we described in Section 3.4, due to the difficulty of aligning source domains, learning the domain-specific representations using ensemble learning will work instead. In 2024, Zhao *et al.* [127] developed an edge-cloud integrated FL framework as shown in Fig. 19, where each client has a classifier that learns only domain-specific knowledge. In local training, the features extracted should be effective not only for the local classifier but also for classifiers on other clients that have not encountered the local data. This approach ensures that the learned features are generalizable across different domains, where the optimization objective for the source client k is as follows:

$$\min_{F^{(k)},G^{(k)}} \mathbb{E}_{x^{(k)},y^{(k)}}\mathscr{L}_{\mathrm{CE}}(G^{(k)}(F^{(k)}(x^{(k)})),y^{(k)}) + \frac{1}{K-1}\sum_{i=1,i\neq k}^{K}\mathbb{E}_{x^{(k)},y^{(k)}}\mathscr{L}_{\mathrm{CE}}(G^{(i)}(F^{(i)}(x^{(k)})),y^{(k)}) \tag{10}$$

where $F^{(k)}(\cdot)$ is a representation learning function for the source client k, and $G^{(k)}(\cdot)$ is its classification function.

There are also novel federated DG fault diagnosis studies that attempt to lift some of the limitations present in traditional federated DG tasks. For example, FL requires the existence of a central server for processing the information uploaded by clients, which may trigger the single-point-of-failure problem. For this reason, in 2024, Xu *et al.* [128] proposed a decentralized federated DG fault diagnosis method that exchanges model weights only between neighboring nodes. Meanwhile, it

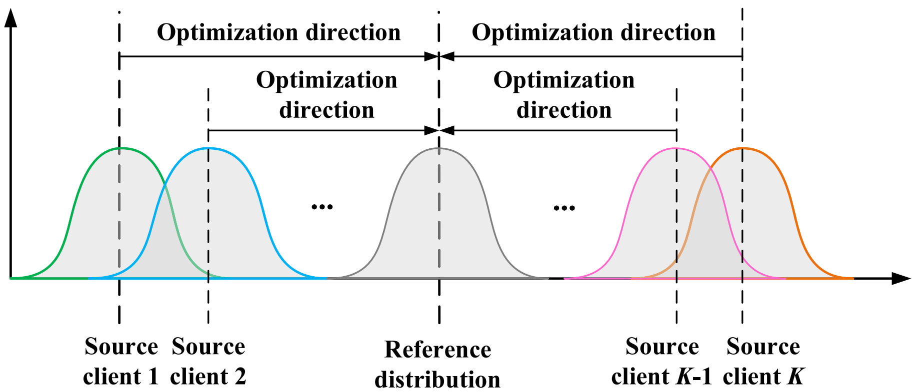

Fig. 18. Reference distribution-based federated DG fault diagnosis methods.

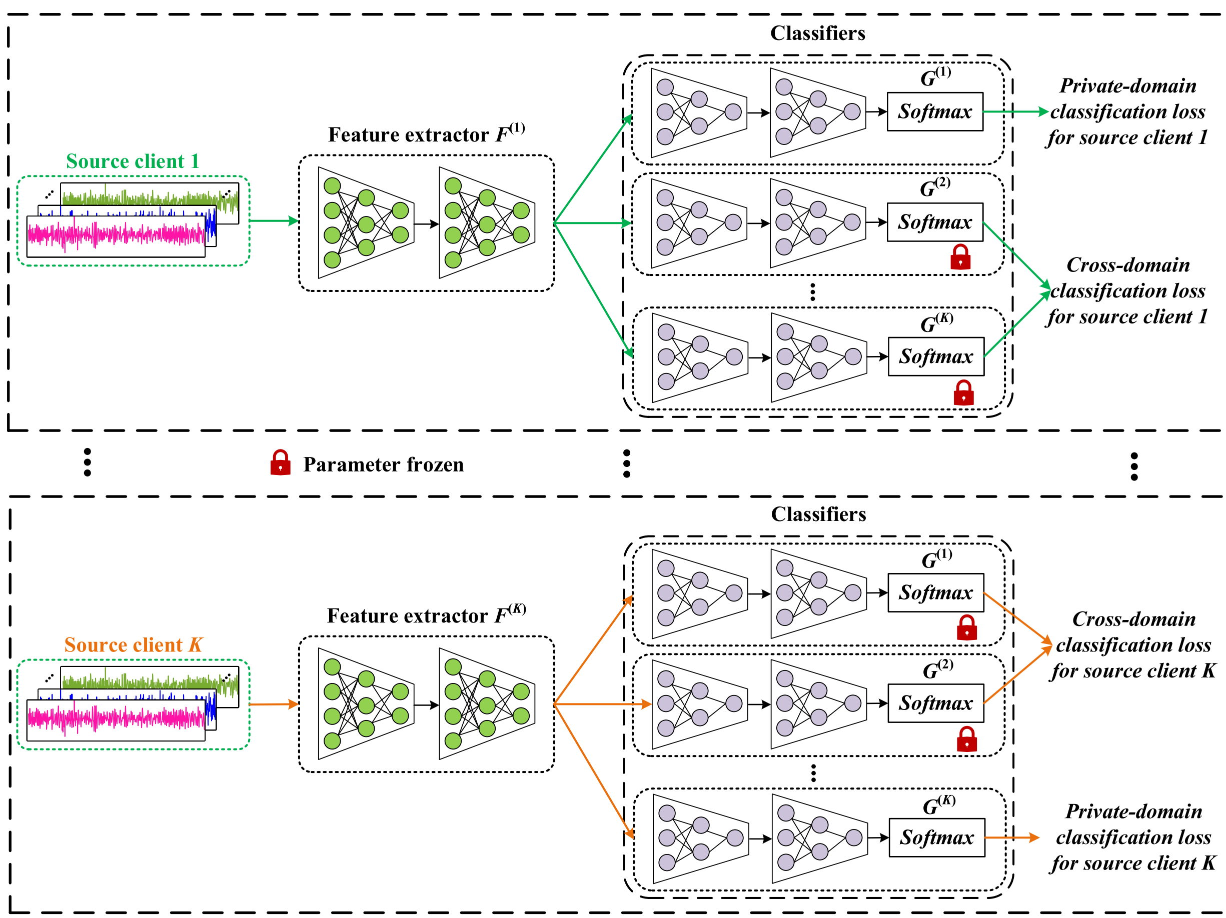

Fig. 19. Ensemble learning-based domain-specific representation extraction for federated DG fault diagnosis [127], where private-domain classification loss for source client k is $\mathbb{E}_{x^{(k)},y^{(k)}}\mathscr{L}_{\mathrm{CE}}(G^{(k)}(F^{(k)}(x^{(k)})),y^{(k)})$, and cross-domain classification loss for source client k is $\sum_{i=1,i\neq k}^{K}\mathbb{E}_{x^{(k)},y^{(k)}}\mathscr{L}_{\mathrm{CE}}(G^{(i)}(F^{(i)}(x^{(k)})),y^{(k)})/K-1$.

exchanges class-cluster statistics to align the representation distributions of neighboring nodes at the class level. In 2024, Qian *et al.* [129] carried out a more novel task called heterogeneous federated DG, in which the source client's data is heterogeneous with the target client's data, e.g., the source client holds gearbox fault data, while the target client holds bearing fault data.

4. Experimental study

In this section, two publicly available datasets are used to examine the diagnostic accuracy of eight typical DG methods for bearing and gearbox (key components of rotating machinery) faults, including AGG, a baseline method that directly aggregates all source-domain data to train a model; four domain alignment methods, DANN, MMD, CORAL, and triplet loss; a data augmentation method, multi-domain Mixup [130]; a *meta*-learning method, MLDG [89]; and an ensemble learning method, DAEL [17]. Note that the comparison experiments are conducted under the setting of multi-source DG fault diagnosis. In addition, due to issues such as hyperparameter selection, dataset adaptation, and method deployment details, the performance of each method in our experiments may not be consistent with its performance in other studies. The accuracy we report for each method is only its baseline accuracy, which implies that they still have enough potential for performance improvement.

Table 3
Network parameters of each module in the diagnostic model.

Components	Layers	Parameters
Feature extractor	Conv-BN-ReLU	out_channels = 16, kernel_size = 25, stride = 2
	Conv-BN-ReLU	out_channels = 32, kernel_size = 15
	Maxpool	kernel_size = 4, stride = 4
	Conv-BN-ReLU	out_channels = 64, kernel_size = 5
	Conv-BN-ReLU	out_channels = 128, kernel_size = 5
	AdaptiveMaxpool	output_size = 4
Classifier	FC-ReLU-Dropout	output_size = 256
	FC-ReLU-Dropout	output_size = 256
	FC	output_size = C
Domain discriminator	FC-ReLU-Dropout	output_size = 1024
	FC-ReLU-Dropout	output_size = 1024
	FC	output_size = K

Conv: convolutional layer; BN: batch normalization; ReLU: ReLU activation function; Maxpool: max pooling layer; AdaptiveMaxpool: adaptive max pooling layer; FC: fully connected layer

Table 3 lists the detailed network parameters of the feature extractor, classifier, and domain discriminator used in the comparison experiments, where the unspecified parameters are set to default values. The main hyperparameters for model optimization are set as follows: the number of epochs is 60, the initial learning rate is 1×10^{-3} with a decay (multiplied by 0.1) in epoch 20 and 40, the inner learning rate for MLDG is 1×10^{-3}, the margin for triplet loss is 0.2, the weight decay is 1×10^{-5}, and the batch size is 32. In addition, we introduce a trade-off parameter to balance the contribution of the cross-entropy loss term and other loss term in each method to the overall optimization objective. In DANN, MMD, and CORAL, this parameter is 0.2, in triplet loss and DAEL it is 0.01, and in MLDG it is 0.1.

4.1. Case 1: Multi-source DG study for gearbox fault diagnosis

1) Data preparation: The dataset used in this case is from PHM Data Challenge Competition 2009 (PHM2009) [131]. This dataset contains a spur gear fault dataset and a helical gear fault dataset, and we use the spur gear fault dataset to conduct the comparison experiments, which is collected by the accelerometers mounted on the output shaft retaining plates at a sampling frequency of 66.67KHz. In addition, this dataset considers eight health states of spur gear (which can be labeled as 0, 1, 2, …, 7), and ten operating conditions in combination of two loads and five rotational speeds. In this paper, data from four operating conditions are chosen to construct four domains, whose rotational speeds are 30 Hz, 35 Hz, 40 Hz, and 45 Hz, respectively, and whose loads are all high load. Following the criterion of leave-one-domain [132], we set up four multi-source DG fault diagnosis tasks, as shown in Table 4. There are a total of 1600 (200 × 8) samples in each source domain and 400 (50 × 8) samples in the target domain, and each sample is 1024 in length and is preprocessed with zero-mean normalization.

2) Result Analysis: Fig. 20 shows the average accuracy of ten replicate trials for each method in each task of Case 1. It can be found that the accuracy of each method in tasks T0 and T3 is considerably lower than its accuracy in tasks T1 and T2. The reason is that the difference in motor speed between the target and source domains is greater in tasks T0 and T3. In addition, although AGG is a baseline method, its accuracy is no less than other comparison methods in some tasks, which suggests that AGG has already yielded impressive results in DG fault diagnosis, and has set a high benchmark for subsequent improved methods. In fact, there is no comparison method that can be more accurate than AGG in all tasks. Despite the highest accuracy in tasks T1 and T2, DAEL has the lowest accuracy in tasks T0 and T3 and is clearly less accurate than the other methods. This indicates that methods that perform better in some tasks are not always applicable to other similar tasks. Mixup achieves the second highest diagnostic accuracy in both tasks T1 and T2, as well as the highest accuracy in task T3. Among the four domain alignment methods, DANN, MMD, CORAL and triplet loss, CORAL has the best performance, while triplet loss has the worst performance, even significantly worse than AGG. MLDG has a slight accuracy improvement compared to AGG in tasks T0, T1, and T2.

Table 4
Details of 4 multi-source DG fault diagnosis tasks in Case 1.

Task code	Source domains (for training)			Target domains (for testing)
	Source 1	Source 2	Source 3	
T0	35 Hz	40 Hz	45 Hz	30 Hz
T1	30 Hz	40 Hz	45 Hz	35 Hz
T2	30 Hz	35 Hz	45 Hz	40 Hz
T3	30 Hz	35 Hz	40 Hz	45 Hz

4.2. Case 2: Multi-source DG study for bearing fault diagnosis

1) Data preparation: The dataset used in this case is a bearing fault dataset provided by Paderborn University (PU) [133]. The piezoelectric accelerometer is mounted on the bearing housing to collect vibration signals at a sampling frequency of 64KHz. There are 32 test bearings, including 6 normal bearings, 12 artificially damaged bearings, and 14 real damaged bearings. In addition, there are four different operating conditions, each of which includes a specific motor speed, radial force on the bearing and load torque on the drive system, as shown in Table 5. In this paper, the condition monitoring signals of 14 real damaged bearings are used to conduct comparison experiments, which can be labeled as 0, 1, 2…, 13. The data from the four operating conditions constitute four domains and result in four DG multi-source DG fault diagnosis tasks as shown in Table 6. There are a total of 2800 (200 × 14) samples in each source domain and 700 (50 × 14) samples in the target domain, and each sample is 1024 in length and is preprocessed with zero-mean normalization.

2) Result Analysis: Fig. 21 shows the average accuracy of ten replicate trials for each method in each task of Case 2. It can be found that tasks T0 and T2 are more challenging compared to tasks T1 and T3. This is due to the significant distribution shifts in tasks T0 and T2, which are caused by the large differences in motor speed and radial force, respectively. In addition, we note that in task T1, the load torque in the source domain is obviously higher than that in the target domain, but task T1 does not show comparable challenge to tasks T0 and T2. This may imply that in PU dataset, motor speed and radial force have a higher impact on the data distribution than load torque. Similar to Case 1, AGG demonstrates diagnostic performance that is not inferior to other comparison methods, and even achieves the highest diagnostic accuracy in task T3. Mixup has the highest accuracy in both tasks T0 and T2. Especially in task T0, it is the only one with an accuracy higher than 40 %. Considering the performance of Mixup in Case 1, it can be assumed that Mixup has great potential for application in DG fault diagnosis. Moreover, CORAL still outperforms the other three domain alignment methods, and it achieves a certain accuracy improvement compared to AGG in tasks T0 and T1. This is consistent with the results in [2] and [134]. Therefore, we recommend using CORAL to align source domains.

5. Challenges and future directions

5.1. How to ensure the effectiveness of the generated latent domains?

Existing DG fault diagnosis studies that use generative models to generate latent domains often aim to ensure the diversity of the latent domains by maximizing the difference between the distributions of the latent domains and the source domains, and simulate the real distribution shifts. However, it is questionable whether training generative models with this objective alone can ensure that the generated domains

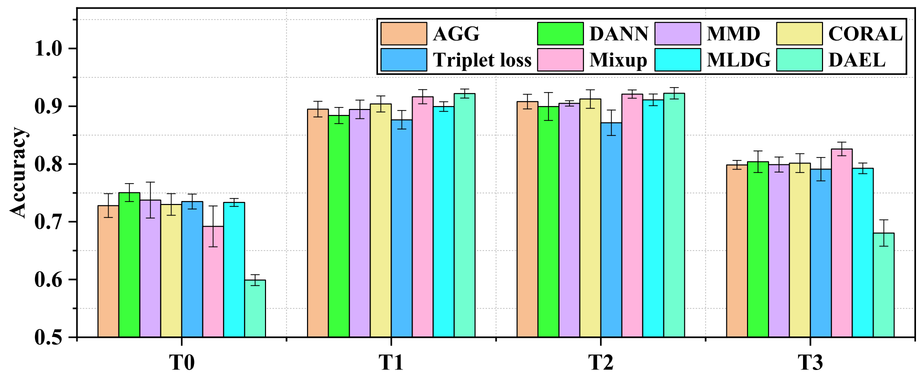

Fig. 20. Average accuracy of ten replicate trials for each method in each task of Case 1.

Table 5
Four operating conditions for the PU dataset.

Operating condition code	Motor speed (rpm)	Load Torque (Nm)	Radial Force (N)
C0	900	0.7	1000
C1	1500	0.1	1000
C2	1500	0.7	400
C3	1500	0.7	1000

Table 6
Details of 4 multi-source DG fault diagnosis tasks in Case 2.

Task code	Source domains (for training)			Target domains (for testing)
	Source 1	Source 2	Source 3	
T0	C1	C2	C3	C0
T1	C0	C2	C3	C1
T2	C0	C1	C3	C2
T3	C0	C1	C2	C3

can be effectively used to guide model training. This is due to the fact that although there are distribution shifts among source domains in real scenarios, there are also inherent similarities among them, which are determined by the fault generation mechanism. Therefore, not all data with distribution differences from the source domains can be considered as latent domains. For example, there are obvious distribution differences between the gearbox fault data and the bearing fault data, but the bearing fault data are difficult to be used directly for training the gearbox fault diagnosis model. Focusing on increasing the difference between the generated domains and the source domains may weaken the validity of the latent domains, which is detrimental to model convergence. Therefore, it is necessary to add more constraints in the optimization process of generative model to capture the inherent similarity between domains while simulating the distribution shifts.

5.2. How the simulation model simulates background noise under real operating conditions?

The use of simulation models to generate simulation data does show great potential for improving the generalization of intelligent diagnostic models. By adjusting the parameters of the simulation model, it is possible to obtain the condition monitoring data of almost any mechanical equipment in any operating mode. However, one of the most critical requirements to achieve this goal is that the simulation model needs to be accurate enough to reflect the real working conditions of the mechanical equipment. In general, the signals collected during the operation of mechanical equipment are accompanied by severe background noise, which is difficult to be modeled in existing studies. In addition, many uncertainties, such as boundary conditions, damping, and component fit, make it difficult to ensure a satisfactory match between the simulation model and the actual physical system. To address this challenge, in addition to the necessary theoretical analysis, it may be useful to utilize some physical experiments to perform a matching analysis with the dynamic response obtained from the simulation model, thus correcting the sensitive parameters in the simulation model.

5.3. Whether "domain-invariant feature" has domain invariance?

Existing domain alignment-based DG fault diagnosis methods aim to map all source domains to a common feature subspace, and treat the features captured in this way as domain-invariant features that can be generalized to unknown target domains. This type of approaches was originated from DA, where the source and unlabeled target domains are mapped to a common subspace, and thus the extracted features are

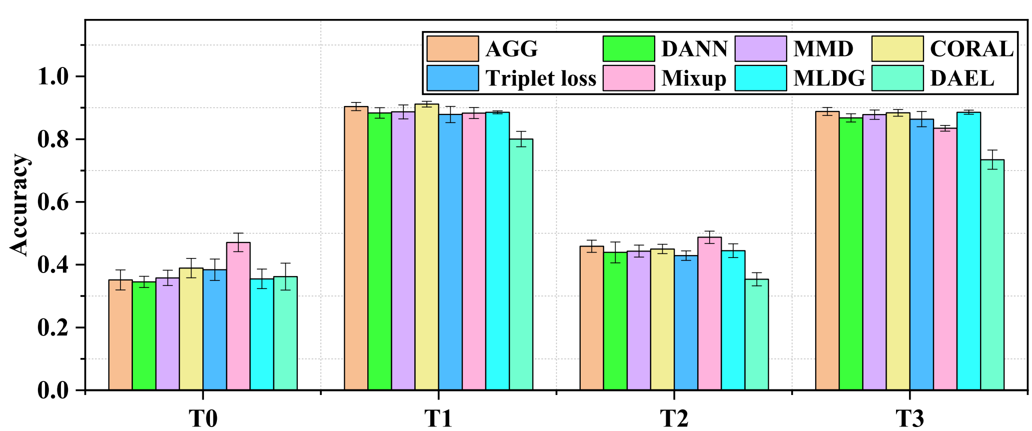

Fig. 21. Average accuracy of ten replicate trials for each method in each task of Case 2.

invariant across the source and target domains, allowing the labeling knowledge of the source domains to be used to process the unlabeled target domains. However, the application of this type of approaches to DG seems to only make the extracted features invariant across source domains, and it is still doubtful whether it is also domain invariant for unknown target domains. This issue may be one of the reasons for the unsatisfactory performance of the domain alignment methods in our two experimental cases. To address this challenge, it is necessary to develop domain alignment methods by searching for feature patterns that are truly invariant across domains from the fault generation mechanism. In addition, combining domain alignment methods with data augmentation methods is also an effective strategy, which makes the domain-invariant features captured by domain alignment methods applicable to a wider variety of latent domains, even including all kinds of unknown target domains.

5.4. Human-model collaborative DG fault diagnosis

Most current DG fault diagnosis studies focus on improving diagnostic accuracy as the goal. For DG fault diagnosis, which is essentially a classification task, it is certainly important to improve the model accuracy. However, focusing solely on the accuracy would seem to imply that the decision of if a mechanical equipment failure occurs is left entirely in the hands of an intelligent model. Even if the model makes untrustworthy diagnostic decisions, the users have no way of knowing that. Whether from an ethical or safety perspective, this lacks consideration. Instead, a trustworthy fault diagnosis model should not only be accurate enough, but should also indicate when its decisions may be incorrect. Therefore, the uncertainty estimation and confidence analysis [135–138] for the result given by the diagnostic model becomes essential. If the result has high confidence and low uncertainty, then it can certainly be used as an important basis for users to make decisions, if the result has low confidence and high uncertainty, then the users should make further comprehensive judgments on the health status of mechanical equipment. Uncertainty estimation and confidence analysis enable users to enter the decision-making loop and achieve collaborative human-model fault diagnosis.

5.5. Continual DG fault diagnosis

The out-of-the-box property of DG models allows them to be directly applied to new target domains without the need to re-train a model for the new target domain as in the case of DA. However, considering that the condition monitoring signals of machines are usually generated in a continuous stream, the new data can be utilized to supplement the DG model with diagnostic knowledge. The approach of combining new data with past data to retrain a model might be effective, but it would be computationally expensive. In addition, further training the original model with new data may result in catastrophic forgetting, i.e., the learned new knowledge interferes with the old knowledge or even completely overwrites it. Therefore, it is necessary to develop techniques on continual learning [139] (also known as incremental or lifelong learning) to be applied to DG fault diagnostic models, so that they can process the continuous stream of signals monitored by the sensors, endowing them with the ability to retain and even optimize the old knowledge while learning new knowledge.

5.6. Multi-modal data fusion

To improve the model's generalization as much as possible, it is necessary to make full use of the various types of monitoring data that can be used to indicate the health status of the machine. These data may be vibration signals, acoustic signals, or thermal images exhibiting multi-modal patterns. Discrepancy and redundancy are expected between them, and it is a challenge to align these multi-modal data, capture complementary features between data of different modalities and remove redundant features. Considering the great success of GPT models based on multi-modal data (text, image, and video), training DG models using multi-modal data is a promising direction.

5.7. Physics-informed generative model

Although generative models such as GAN relax the dependence of physical simulation models on physical knowledge, the patterns of their generated samples are highly correlated with the original samples. When the diversity of source-domain samples is insufficient, the generated samples may also face the problem of homogeneous patterns, making it difficult to satisfy the demand for samples with various operating conditions as flexibly as physical simulation models. Meanwhile, it is challenging for physical simulation models to capture the real background noise information by analyzing real samples as generative models do, which makes their generated samples often too pure. Therefore, it may be useful to consider building physics-informed generative models by embedding physical knowledge into generative models, as in the case of physics-informed neural networks [140], so as to generate a large number of samples that are pattern-rich, physically meaningful, and reflective of the real background noise, addressing the problem of "data starvation".

6. Conclusion

In this paper, we first categorize current DG fault diagnosis studies in general by task type, and then further subdivide the studies under each task based on the underlying methodology. Subsequently, this paper summarizes the core ideas of each methodology and follows with a comprehensive review of DG fault diagnosis studies that rely on that methodology, as well as insights into other potential solutions. Then, this paper validates the diagnostic performance of various typical DG methods using two publicly available datasets. Finally, we offer suggestions for promising future research directions and hope that this will encourage more novel research on DG fault diagnosis.

CRediT authorship contribution statement

Yiming Xiao: Writing – original draft, Software, Formal analysis. **Haidong Shao:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Shen Yan:** Validation, Data curation. **Jie Wang:** Visualization, Investigation. **Ying Peng:** Investigation, Data curation. **Bin Liu:** Writing – review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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