

## Recent advances in generative adversarial networks for vibration data generation in rotating machine fault diagnosis: A comprehensive review

Yinlong Yeng<sup>1</sup>, Mohammad Khalid Husain<sup>2</sup>

<sup>1</sup>School of Electronic Engineering, Xidian University, Xi'an 710071, China

<sup>2</sup>Associate Professor, General Education Department, Effat College of Humanities, Effat University, Saudi Arabia

**Received:** 01-Jan-2026, Manuscript No. JPAI-26-0002; **Editor assigned:** 03-Jan-2026, PreQC No. JPAI-26-0002 (PQ); **Reviewed:** 15-Jan-2026, QC No. JPAI-26-0002; **Revised:** 22-Jan-2026, Manuscript No. JPAI-26-0002 (R); **Published:** 03-Feb-2026

Citation: YENG Y, HUSAIN MK (2026). Recent advances in generative adversarial networks for vibration data generation in rotating machine fault diagnosis: A comprehensive review. J Prog Artif Intell.

Copyright: © 2026 YENG Y, HUSAIN MK. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited

**Corresponding:** Yinlong Yeng, E-mail: Ylong@Yeng.edu.cn

### ABSTRACT

Fault diagnosis of rotating machinery plays a pivotal role in ensuring operational reliability, efficiency, and productivity in modern manufacturing systems. However, limited fault samples and class imbalance issues impede the effective development and deployment of fault diagnosis models. Generative adversarial networks (GANs) and their variants have emerged as promising solutions to these challenges, and studies in this research field are expanding. However, the latest GAN variants specifically applied to vibration data generation for fault diagnosis have not been systematically reviewed. Moreover, the existing literature lacks a comprehensive evaluation of the quality metrics used to assess GAN-generated vibration data and inadequately addresses the practical challenges faced in industrial settings. Therefore, this

paper provides a review of the latest studies on the applications of GANs and their variants for generating vibration data in the fault diagnosis of rotating machines. The review begins with an overview of the basic structure and principles of standard GANs and recent advancements, followed by a detailed analysis of their applications in generating synthetic vibration data for fault diagnosis. It then reviews the metrics employed to evaluate the quality and diversity of GAN-generated vibration data. Finally, this review provides practical considerations, ongoing challenges, recent advancements, and future directions. The insights shared in this review can guide researchers and practitioners in this rapidly evolving field.

**Keywords:** Generative adversarial networks, vibration data generation, rotating machinery, fault diagnosis, synthetic data.

### INTRODUCTION

Rotating machines are essential components of modern industrial manufacturing systems. These machines drive a wide range of critical processes and

operations. However, continuous operation and exposure to various cyclic loading conditions render these machines susceptible to mechanical failure. Such failures can result in production losses, diminished competitiveness, and potential safety hazards [1, 2]. Consequently, proactive health monitoring and early

diagnosis of faults in these machines are vital to ensuring reliability, reducing downtime, and minimizing maintenance costs, thereby enhancing the overall efficiency and productivity of the manufacturing ecosystem.

Vibration analysis is widely acknowledged as a reliable and non-invasive technique for monitoring the health of rotating machines. By analyzing the vibration signatures produced by these machines, researchers and engineers can identify early signs of degradation, diagnose the root causes of faults, and implement appropriate remedial actions [3, 4]. However, obtaining sufficient and representative vibration data samples presents significant challenges due to environmental complexity, difficulties in sensor placement, operational variability, intermittent faults, data acquisition limitations, maintenance practices, safety and access constraints, and organizational/resource limitations. The issue of limited data can lead to model overfitting, where a fault diagnosis system performs well with familiar training examples but struggles to accurately classify new, previously unseen instances [5] a problem exacerbated by deep learning models. The small sample issue is further complicated by the data imbalance problem, in which data from normal operations is abundant, while data from faulty conditions is scarce. This discrepancy in training samples hinders fault diagnosis models from learning the distinctive features of faulty conditions, thereby limiting diagnostic accuracy and stability [6].

To tackle the problems of limited fault data availability and the imbalance between fault and normal data, researchers have developed and employed various data augmentation techniques. In the literature, oversampling methods have been widely used to synthesize additional minority class samples and balance the data distribution. For instance, Diaz [7] utilized the synthetic minority oversampling method to generate extra fault samples, leading to improved fault diagnosis accuracy. Zhang et al. [8] employed a weighted minority oversampling technique to achieve data distribution balance. Yao et al. [9] combined a sample-characteristic oversampling method with a multi-class least squares SVM to address limited training data and imbalanced datasets in bearing fault diagnosis. Zhang and Li [10] introduced a random walk-oversampling method to rectify the class imbalance issue. In addition to oversampling, data transformation techniques have been explored to artificially expand the available data. These methods implement transformations such as rotation, scaling, and noise injection on existing samples, resulting in augmented versions [11-13]. By utilizing these data augmentation

strategies, fault diagnosis systems become exposed to a broader set of fault-related patterns, thereby enhancing their generalizability and diagnostic accuracy.

To address the issues of the limited availability of fault data and the imbalance between fault and normal data, researchers have developed and employed various data augmentation techniques. In the literature, oversampling techniques have been widely utilized to synthesize supplementary minority class samples and balance the data distribution. For example, Diaz [7] utilized the synthetic minority oversampling method to generate additional fault samples, resulting in improved fault diagnosis accuracy. Zhang et al. [8] employed a weighted minority oversampling technique to balance the data distribution. Yao et al. [9] hybridized a sample-characteristic oversampling method with a multi-class least squares SVM to address limited training data and imbalanced datasets in bearing fault diagnosis. Zhang and Li [10] presented a random walk-oversampling method to address the issue of class imbalance. In addition to oversampling, data transformation practices have been explored to artificially expand the available data. These methods apply transformations such as rotation, scaling, and noise injection to existing samples, producing augmented versions [11-13]. By employing these data augmentation strategies, fault diagnosis systems gain exposure to a richer set of fault-related patterns, thereby improving their generalizability and diagnostic accuracy.

However, the aforementioned data augmentation methods have limitations, one of which is a lack of adaptability. Fortunately, advances in generative models, particularly Generative Adversarial Networks (GANs), have provided a promising solution to this challenge. GAN was initially proposed by Goodfellow et al. [14] in 2014 for computer vision applications. Building on this seminal work, Lee et al. [15] pioneered the application of GAN to motor fault detection with limited fault data in 2017. The applications of GANs in fault diagnosis expanded in 2018 when they were employed to diagnose bearing faults [16]. Wang et al. [17] further advanced this field by using a GAN to generate synthetic fault signals, which were then utilized alongside a stacked denoising autoencoder for the fault diagnosis of planetary gearboxes. Following these initial successes, research on GANs and their variants for generating fake vibration data in fault diagnosis has rapidly gained momentum [18, 19].

Before this work, several reviews have examined GANs and their applications across various fields. The earliest significant review is likely by Chakraborty et al. [20],

which surveyed a decade of development in GANs. Other reviews [21, 22] also offered a literature review on the foundational background, theoretical frameworks, and extended variants of GANs. Additionally, there are surveys focused on the application of GANs in specific domains, such as medical image analysis [23], earthquake-related engineering [24], materials science [25], and prognostic and health monitoring tasks [26]. Other relevant reviews can be found in [27-30].

Despite the growing body of research on GAN applications in fault diagnosis, comprehensive reviews in this rapidly evolving field remain limited compared to those in other areas. Li et al. [31] reviewed how GANs can generate data to address the scarcity of real-world fault data and class imbalances in fault diagnosis. Pan et al. [32] examined the use of GANs in fault diagnosis under small sample scenarios, presenting model architecture, loss functions of the GANs, and future perspectives. Ruan et al. [33] assessed GAN advancements for synthetic data generation in bearing fault diagnosis, including evaluation metrics for synthesized samples. Liao et al. [34] provided a comprehensive review of GANs in the fault diagnosis of mechanical devices. Additional review articles have touched upon GANs in fault diagnosis, although not as their primary focus [35, 36]. These contributions have laid important groundwork, but the initial bibliographic analysis uncovers several limitations: (1) Existing reviews do not offer an overview of the latest GAN variants, such as the relativistic GAN, CycleGAN, and progressive GAN; (2) there is limited exploration of GANs for generating time-series vibration data and their integration with advanced techniques, such as attention mechanisms, transfer learning, meta-learning, few-shot learning, and zero-shot learning; (3) existing reviews do not thoroughly evaluate GAN-generated vibration data in terms of fidelity, diversity, and suitability for fault diagnosis tasks; (4) practical considerations and ongoing research challenges in GAN-based approaches in real-world industrial settings are not fully addressed; and (5) most importantly, **REVIEW METHODOLOGY**

#### *Data Selection Process*

In this review, the authors adopted comprehensive and systematic approaches to identify, select, and critically

existing reviews inadequately cover the latest advancements and potential research directions in GANs for vibration-based fault diagnosis, particularly concerning small fault data samples and class imbalance issues.

To address these knowledge gaps, this paper presents a comprehensive and up-to-date review of how GANs are applied in the fault diagnosis of rotating machines. The review explores the following research questions (RQs):

RQ1. What are the fundamental structures and principles of the original GAN and its advanced variants?

RQ2. What are the applications of GANs in generating time-series vibration data, and how can they be integrated with advanced techniques such as attention mechanisms, transfer learning, meta-learning, few-shot learning, and zero-shot learning for fault diagnosis?

RQ3. How can the quality of GAN-generated vibration data be evaluated in terms of fidelity, diversity, and suitability for fault diagnosis tasks?

RQ4. What practical considerations and challenges are involved in deploying GAN-generated vibration data in real-world industrial settings for fault diagnosis applications?

RQ5. What are the latest advancements and future research directions that address the existing challenges and limitations in GAN-based vibration data generation for fault diagnosis studies?

RQ1 is discussed in Section 0, RQ2 is explored in Section 0, RQ3 is examined in Section **Error! Reference source not found.**, **Error! Reference source not found.** is detailed in Section 0, and **Error! Reference source not found.** is covered in Section **Error! Reference source not found.**

appraise the relevant studies. The literature search was conducted in two prominent indexing databases: Scopus and Web of Science. The search query keywords combine major terms with their synonyms using Boolean operators (AND, OR), as shown in

Table 1.

Table 1. Search query terms.

Major terms	Search terms
Limited sample size and imbalanced data	((“small sample size” OR “limited data” OR “insufficient data” OR “class imbalance” OR “unbalanced data” OR “skewed data”) AND
Generative adversarial network	(“generative adversarial network” OR “GAN”) AND
Data generation	(“data generation” OR “data augmentation” OR “data synthesis”) AND
Vibration data	(“vibration data” OR “vibration signal”) AND
Fault diagnosis	(“fault diagnosis” OR “fault classification” OR “fault detection”) AND
Rotating machine	(“rotating machine” OR “rotating machinery” OR “rotating equipment”))

The literature search began in 2014, marking the development of the GAN [14]. However, the use of GANs in fault diagnosis was not introduced until 2017 [15]. The review considers journal articles, conference papers, review papers, and book chapters written in English. Article preprints, publications available only as abstracts, and studies deemed unrelated to the scope of the review were excluded. To ensure comprehensive coverage, the reference lists of identified papers were manually checked using a backward snowballing technique [37]. Finally, this systematic process led to the

selection of 209 documents for further synthesis and categorization.

#### *Bibliographic analysis*

The publishing trend from 2017 to 2024 is illustrated in Figure 1. The number of publications has increased exponentially due to the emergence and application of new GAN variants in this field. This quantitative evidence suggests that this review represents a crucial research area and is likely to remain a focal point in the years ahead

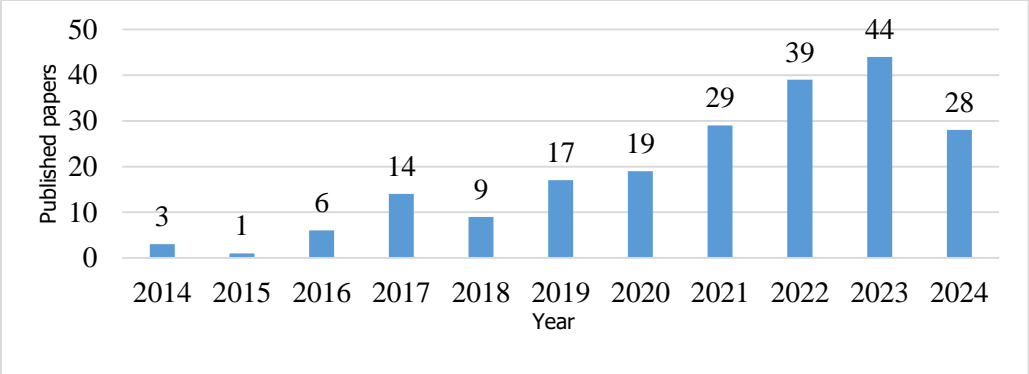


Figure 1. Trends in publishing by year from 2017 to 2024.

In the analysis of the selected papers, original articles made up the majority, totaling 153 documents. Additionally, there were 32 conference papers and 21 review articles. The remaining three documents were categorized as book chapters. This distribution highlights the predominance of original research within the collection, as depicted in Figure 2.

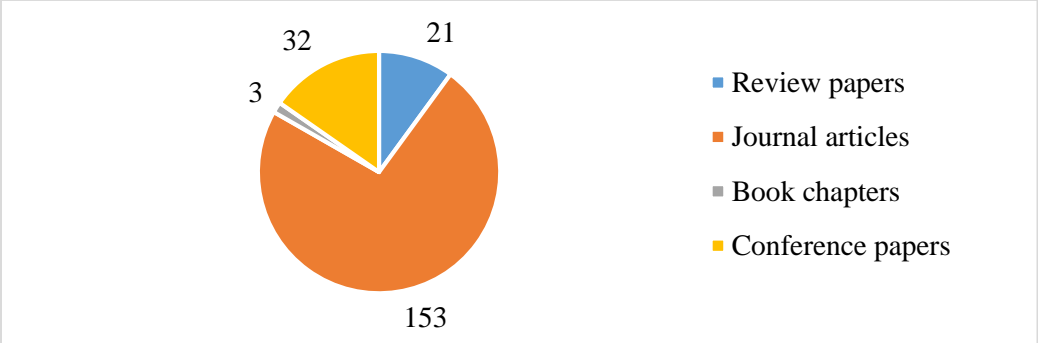


Figure 2. Analysis of selected documents by type of article.

The documents are further analysed by territory, as shown in Figure 3. China emerges as the leading country, with 142 publications, followed by the USA with 32 publications and Canada with 13 publications. These results indicate that the birth of GAN and its variants originated in Western countries, and their applications are being increasingly explored in Eastern contexts.

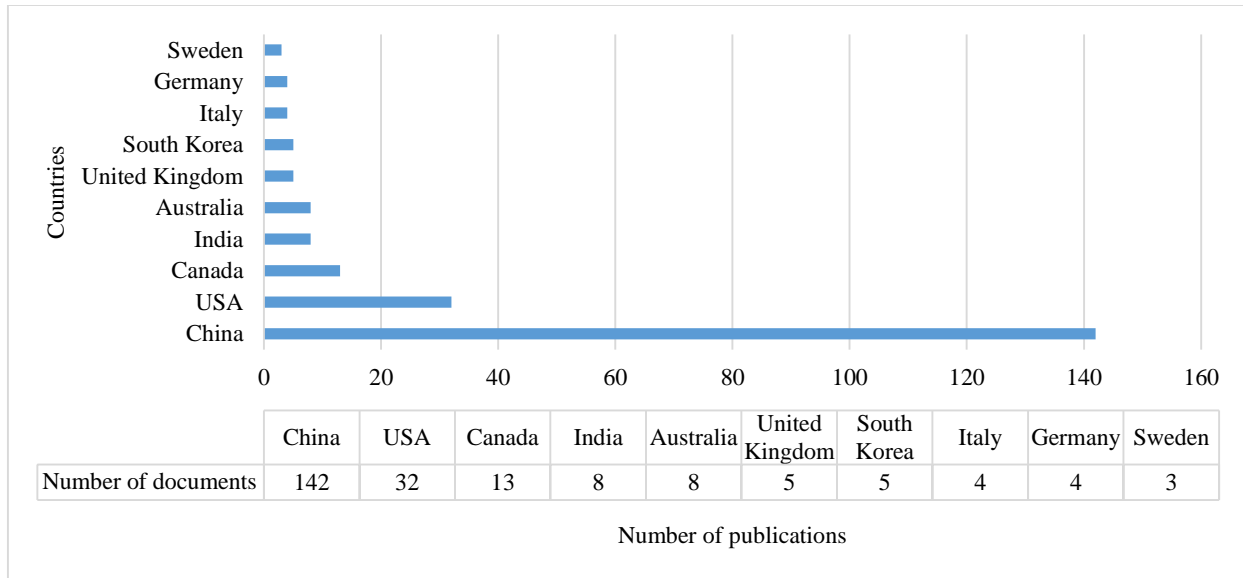


Figure 3. The top ten countries by number of publications.

To further examine the role of industry, an analysis was conducted. Figure 4 shows the distribution of publications by sector, revealing that 170 documents originated from academia. In contrast, industry

contributions account for only 7 publications, while collaborative efforts between academia and industry result in 31 publications. This illustrates the limited influence of industry in the field.

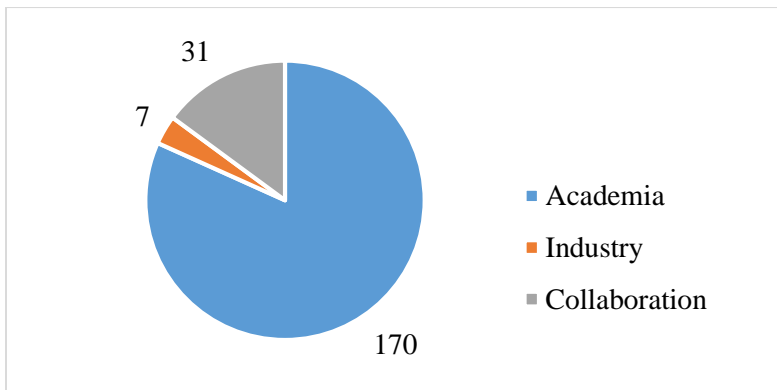


Figure 4. Number of publications by sector.

### Overview of Generative Adversarial Networks

This section provides an overview of the fundamental structure and principles of a GAN and its variants, addressing the first research question (RQ1).

**Basic Structure and Principles of GAN :** The generative adversarial network (GAN) consists of a generator, denoted as  $G$ , and a discriminator, denoted as  $D$ , as illustrated in Figure 5. The generator takes a random noise vector  $z$  as input and generates synthetic data  $G(z)$  that aims to imitate real data  $x$ . Meanwhile, the discriminator's role is to differentiate between real data  $x$  and fake data  $G(z)$ .

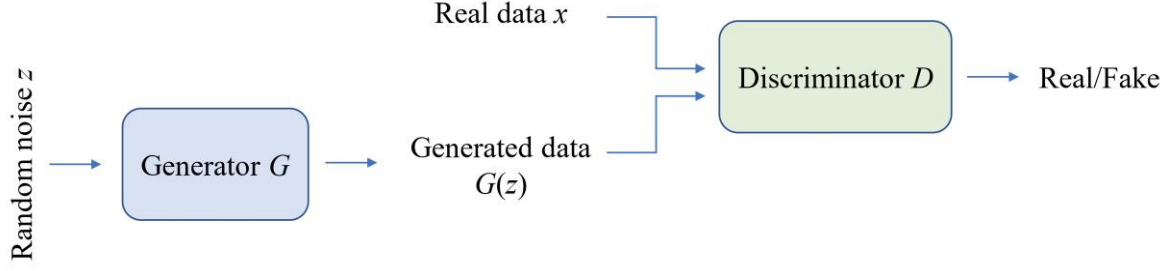


Figure 5. Typical structure of a standard GAN.

The training process involves an iterative adversarial game where the generator and discriminator compete against each other. The generator tries to minimize the objective function  $V(D, G)$ , while the discriminator seeks to maximize it. This process continues until the model reaches Nash equilibrium, at which point the GAN attains its optimal performance. The objective function of the GAN can be expressed as:

$$\min_G \max_D V(D, G) = E_{x \sim P_{data}(x)} [\log D(x)] + E_{z \sim P_{noise}(z)} [\log (1 - D(G(z)))] \quad (1)$$

where  $E$  is the expectation operator,  $P_{data}(x)$  is the data distribution of actual data  $x$ ,  $D(x)$  is the output probability of the discriminator for real data  $x$ ,  $P_{noise}(z)$  is the distribution of random noise input  $z$ , and  $D(G(z))$

$$\min_G \max_D V(D, G) = E_{x \sim P_{data}(x)} [D(x)] - E_{z \sim P_{noise}(z)} [D(G(z))] \quad (2)$$

Here,  $D(x)$  is the output of the discriminator for real data  $x$ , and  $D(G(z))$  is the output of the discriminator for generated data  $G(z)$ . Unlike the original GAN loss, the WGAN removes log functions because the Wasserstein distance provides a more stable learning signal [39].

Although the training process of the WGAN is more stable and faster than that of the standard GAN, it may still encounter difficulties in generating high-quality samples or achieving convergence due to the weight clipping applied to the discriminator. To address this limitation, Gulrajani et al. [40] proposed WGAN-GP, which includes a gradient penalty strategy. The objective function of the WGAN-GP can be expressed as:

$$\min_G \max_D V(D, G) = \underbrace{E_{x \sim P_{data}(x)} [D(x)] - E_{z \sim P_{noise}(z)} [D(G(z))]}_{\text{Objective function of WGAN}} - \underbrace{\lambda E_{\hat{x} \sim P_{\hat{x}}} [(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2]}_{\text{Penalty term}} \quad (3)$$

is the output probability of the discriminator for generated data  $G(z)$ .

### Recent Advancements in GAN Models

#### Wasserstein GAN

The standard GAN employs Jensen–Shannon (J-S) divergence to quantify how different the real and fake data distributions are. However, the J-S divergence becomes constant when the distributions are far apart, which leads to vanishing gradients during training. To address this problem, Arjovsky et al. [38] introduced the Wasserstein GAN (WGAN). The WGAN uses the Wasserstein distance to evaluate the divergence between actual and fake samples, providing a more stable learning signal. The objective function of the WGAN can be articulated as:

where  $\hat{x}$  represents a random interpolation of real and fake data distributions, and  $\lambda$  is the penalty coefficient.

#### Least Squares GAN

Least squares GAN (LSGAN) is a modified version of the standard GAN proposed by Mao et al. [41]. Instead of using binary cross-entropy loss, the LSGAN employs a least squares loss function. This method measures how far the generated data is from the real data and how different the discriminator's outputs are from the target values for real and fake data. The objective functions for the discriminator and generator in the LSGAN can be expressed as follows:

$$\min_D V(D) = \frac{1}{2} E_{x \sim P_{data}(x)} [(D(x) - b)^2] + \frac{1}{2} E_{z \sim P_{noise}(z)} [D((G(z)) - a)^2] \quad (4)$$

$$\min_G V(G) = \frac{1}{2} E_{z \sim P_{noise}(z)} [(D(G(z)) - c)^2] \quad (5)$$

where  $a$  is the target value for fake data,  $b$  is the target value for real data, and  $c$  is the value that the generator aims to match.

For a linear discriminator  $D(x) = w^T x + b$ , where  $w$  and  $b$  are the weights and bias, respectively, the objective functions can be rewritten as:

$$\min_D V(D) = \frac{1}{2} E_{x \sim P_{data}(x)} [(w^T x + b - b)^2] + \frac{1}{2} E_{z \sim P_{noise}(z)} [(w^T G(z) + b - a)^2] \quad (6)$$

$$\min_G V(G) = \frac{1}{2} E_{z \sim P_{noise}(z)} [(w^T G(z) + b - c)^2] \quad (7)$$

This formulation of the LSGAN objective function is equivalent to minimizing the Wasserstein distance between real and fake data distributions, up to a

constant. As a result, researchers often view the LSGAN as a variant of the WGAN.

#### Deep Convolutional GAN

The original GAN architecture employs fully connected layers, which significantly restrict its ability for effective feature extraction and hinder training efficiency. To address these limitations, Radford et al. [42] Developed The Deep Convolutional GAN (DCGAN), which utilizes a Convolutional Neural Network (CNN) as the primary component for the discriminator and generator networks, as illustrated in Figure 6. This design choice leverages the inherent advantages of CNNs, which can enhance performance. Specifically, the weight-sharing property enables networks to learn local patterns and features more effectively, while the local connectivity of convolutional layers also resembles the human visual system.

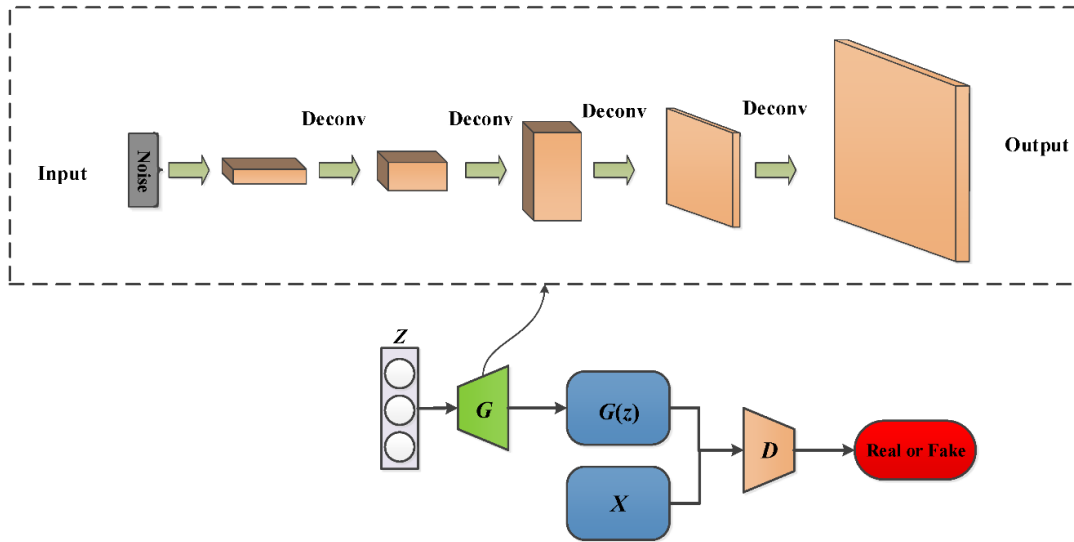


Figure 6. Structure of the DCGAN [43].

#### Conditional GAN

The original GAN uses unrestricted random noise as input, which can lead to mode collapse—a problem where the generator synthesizes only a limited subset of desired outputs. To address this issue, Mirza et al. [44] developed the conditional GAN (cGAN). Unlike the original GAN, the cGAN takes two inputs: a random noise vector  $z$  and a conditional variable  $c$  (see Figure 7). This conditional variable  $c$  provides additional information to control and stabilize the data generation process. The objective function for the cGAN can be mathematically expressed as [45]:

$$\min_G \max_D V(D, G) = E_{x \sim P_{data}(x)} [\log D(x|c)] + E_{z \sim P_{noise}(z)} [\log (1 - D(G(z|c)))] \quad (8)$$

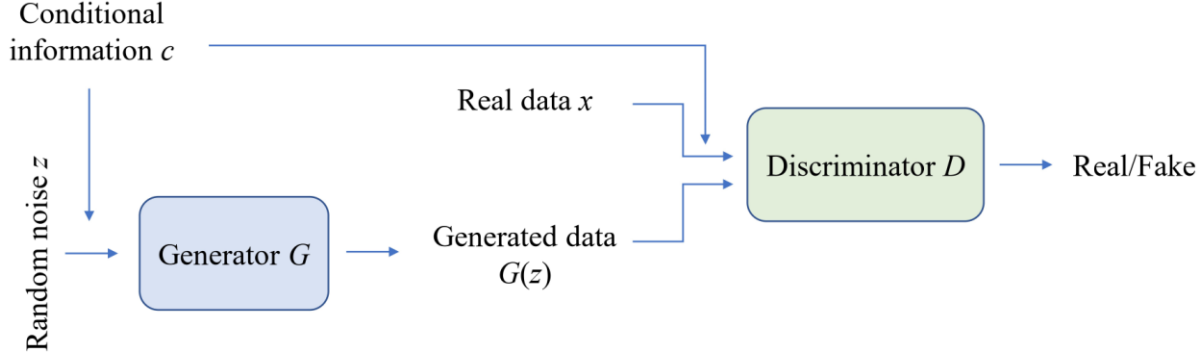


Figure 7. Structure of the cGAN.

Building upon the cGAN, two more advanced cGAN models have been proposed: the information maximizing GAN (infoGAN) and the auxiliary classifier GAN (ACGAN). InfoGAN, proposed by Chen et al. [46] in 2016, can learn disentangled and interpretable latent representations in an unsupervised manner. InfoGAN uses a latent representation vector  $c$  instead of an explicit conditional variable. As shown in Figure 8, InfoGAN adds an auxiliary classifier  $Q$ , and its objective function can be expressed as:

$$\min_G \max_D V(D, G, Q) = E_{x \sim P_{data}(x)} [\log D(x|c)] + E_{z \sim P_{noise}(z)} [\log (1 - D(G(z|c)))] - \lambda I(c; G(z, c)) \quad (9)$$

where  $I(c; G(z, c))$  is the mutual information between the latent vector  $c$  and the output of the generator  $G(z, c)$ , and  $\lambda$ , which is  $> 0$ , is a hyperparameter controlling the balance between the adversarial loss and the mutual information regularization.

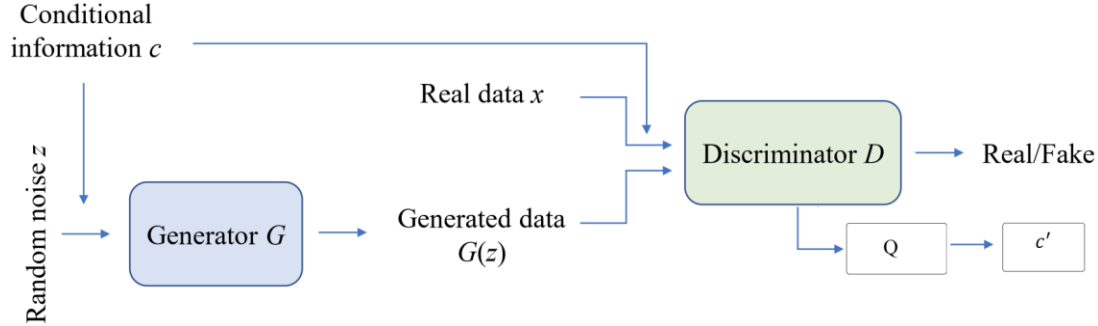


Figure 8. Structure of the InfoGAN.

The conditional GAN (cGAN) trains the discriminator solely to differentiate between real and fake data; however, it lacks an explicit mechanism for classifying input samples into their respective class labels. To address this limitation, Odena et al. [47] developed the auxiliary classifier GAN (ACGAN) in 2017. In the ACGAN framework, generator  $G$  receives two inputs: the typical random noise vector  $z$  and the desired class label  $c$  for conditioning the generated sample (Figure 9). The discriminator  $D$ , in turn, produces two outputs: a traditional binary classification to distinguish between real and fake data and an auxiliary classifier output  $C$  that predicts the class label  $c'$  for the input data. The objective function for ACGAN can be expressed as:

$$\min_G \max_D V(D, C, G) = E_{x \sim P_{data}(x)} [\log D(x) + \log C(c|x)] + E_{z \sim P_{noise}(z)} [\log (1 - D(G(z|c)))] + \log C(c'|G(z)) \quad (10)$$

In this equation,  $C(c|x)$  is the result of the auxiliary classifier for the class label of real data, and  $C(c'|G(z))$  is the output of the auxiliary classifier for the class label of generated data.

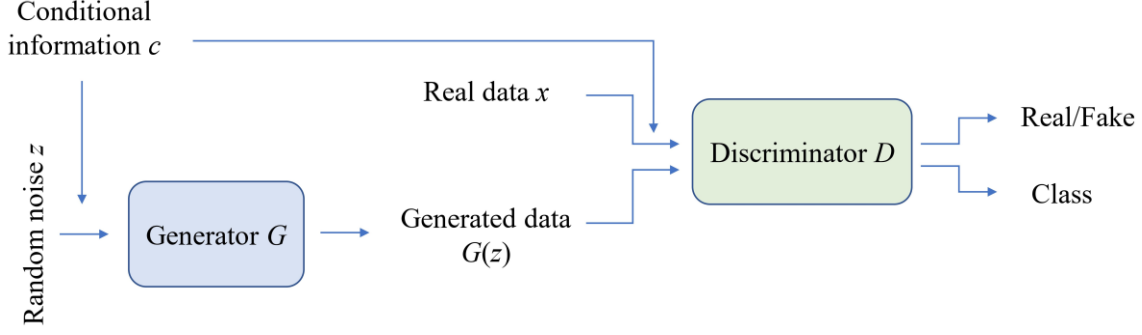


Figure 9. Structure of the ACGAN.

### Semi-Supervised GAN

The Semi-Supervised GAN (SSGAN) is an extension of the standard GAN, designed to address scenarios where labeled data are scarce [48]. In the SSGAN, the discriminator is transformed from a binary classifier (i.e., real vs. fake) into a multi-class classifier. The discriminator now outputs  $K + 1$  classes, where  $K$  is the number of real data classes, and the  $(K + 1) - th$  class represents the generated data. Unlike the original GAN, the SSGAN leverages unlabeled data samples by constructing pseudo-labels, which are then used to train the discriminator. This approach expands the available training data, reducing reliance on labeled samples. The structure of the SSGAN is shown in Figure 10.

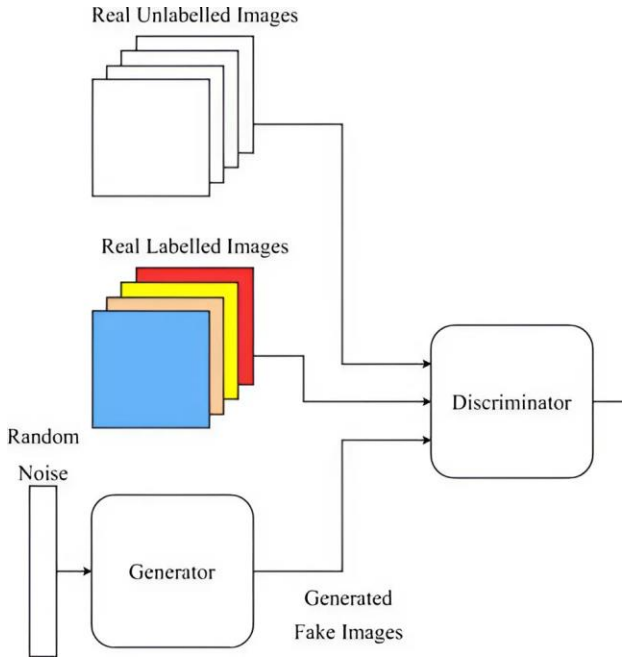


Figure 10. Structure of the SSGAN, with  $K$  classes of real data and an additional  $(K + 1) - th$  class for generated synthetic data [49].

The objective function for the SSGAN is expressed as:

$$\min_G \max_D V(D, G) = V_{supervised}(D, G) + V_{unsupervised}(D, G) \quad (11)$$

Here, the supervised loss term,  $V_{supervised}(D, G)$ , for labeled data, can be stated as:

$$V_{supervised}(D, G) = E_{x, y \sim P_{data}(x, y)} [\log D(y|x)] + E_{z \sim P_{noise}(z)} [\log(1 - D(k + 1|G(z)))] \quad (12)$$

The unsupervised loss term,  $V_{unsupervised}(D, G)$ , involves the unlabeled data samples, and can be expressed as:

$$V_{unsupervised}(D, G) = E_{x \sim P_{data}(x)} [\log(\max_k D(k|x))] + E_{z \sim P_{noise}(z)} [\log(1 - D(k + 1|G(z)))] \quad (13)$$

In the equations above,  $P_{data}(x, y)$  is the joint distribution of the labeled data samples,  $P_{data}(x)$  is the distribution of the unlabeled data samples,  $P_{noise}(z)$  is the noise distribution,  $D(y|x)$  is the probability of the true class  $y$  given the input  $x$ , as predicted by the discriminator,  $D(k|x)$  is the probability of the  $k - th$  class given the input  $x$ , as predicted by the discriminator, and  $D(k + 1|G(z))$  is the probability of the fake class, as predicted by the discriminator for the fake samples.

### Energy-Based GAN

The energy-based GAN (EBGAN), introduced by Zhao et al. [50] in 2016, departs from traditional binary classification of real versus fake samples. Instead, the EBGAN employs an autoencoder-based discriminator that assigns energy scores to real data and high energy scores to fake data. The loss functions are defined as follows:

$$L(D) = E_{x \sim P_{data}(x)} [D(x) + [m - D(G(z))]^+] \quad (14)$$

$$L(G) = E_{z \sim P_{noise}(z)} [D(G(z))] \quad (15)$$

where  $D(x)$  is the energy score assigned by the discriminator to input  $x$ ,  $m$  is a positive margin, and  $G(z)$  is the generator output for the latent input  $z$ .

#### Boundary Equilibrium GAN

The boundary equilibrium GAN (BEGAN), proposed by Berthelot et al. [51] in 2017, improves upon the EBGAN. Like the EBGAN, the BEGAN utilizes an encoder-decoder structure for the discriminator but introduces an equilibrium-enforcing algorithm to balance the training of the generator and discriminator. The BEGAN loss functions are defined as follows:

$$L(D) = E_{x \sim P_{data}(x)} [\|x - D(x)\|] - k_t E_{z \sim P_{noise}(z)} [\|x - D(G(z))\|] \quad (16)$$

$$L(G) = E_{z \sim P_{noise}(z)} [\|x - D(G(z))\|] \quad (17)$$

The CycleGAN architecture includes two generators ( $G$  and  $F$ ) and two discriminators ( $D_X$  and  $D_Y$ ), as shown in Figure 11. The generator  $G$  learns to transform images from domain  $X$  to domain  $Y$ , while the

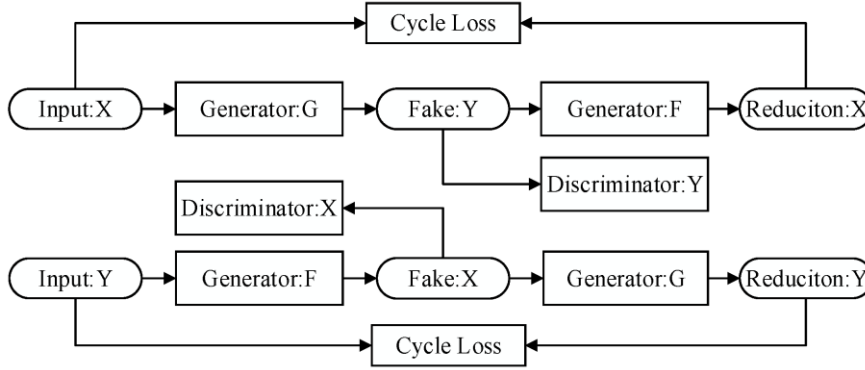


Figure 11. Structure of the CycleGAN [53].

The objective function of CycleGAN can be defined as:

$$\min_{G, F} \max_{D_X, D_Y} V(G, F, D_X, D_Y) = L_{GAN}(G, D_Y, X, Y) + L_{GAN}(F, D_X, Y, X) + \lambda_{cyc} L_{cyc}(G, F) \quad (19)$$

where  $L_{GAN}(G, D_Y, X, Y)$  is the GAN loss for generator  $G$  and discriminator  $D_Y$ , which can be expressed as:

$$L_{GAN}(G, D_Y, X, Y) = E_{y \sim p_{data}(y)} [\log D_Y(y)] + E_{x \sim p_{data}(x)} [\log(1 - D_Y(G(x)))] \quad (20)$$

$L_{GAN}(F, D_X, Y, X)$  is the GAN loss for generator  $F$  and discriminator  $D_X$ , which can be written as:

where  $k_t$  is the dynamic variable that is updated to balance the generator and discriminator.

The key aspect of BEGAN is the equilibrium enforcing algorithm, which updates the weighting coefficient  $k_t$  during training. The updated rule for  $k_t$  can be expressed as:

$$k_{t+1} = k_t + \lambda_k (\gamma E_{x \sim P_{data}(x)} [\|x - D(x)\|] - E_{z \sim P_{noise}(z)} [\|x - D(G(z))\|]) \quad (18)$$

where  $\lambda_k$  is the proportional gain for updating  $k_t$ , and  $\gamma$  is a weighting coefficient in the update rule for  $k_t$ .

#### Cycle-Consistent GAN

The Cycle-Consistent GAN (CycleGAN) is a prominent architecture for unpaired image-to-image translation. Unlike standard GANs, which require paired input-output data for training, CycleGAN can learn mappings between two visual domains without explicitly paired examples. This capability makes CycleGAN valuable for situations where obtaining paired data is challenging or infeasible.

generator  $F$  learns the inverse mapping from  $Y$  to  $X$ . For a more comprehensive explanation, readers are referred to the study by Zhu et al. [52].

$$L_{GAN}(F, D_X, Y, X) = E_{x \sim p_{data}(x)} [\log D_X(x)] + E_{y \sim p_{data}(y)} [\log(1 - D_X(F(y)))] \quad (21)$$

$L_{cyc}$  is the cycle-consistency loss, which can be written as:

$$L_{cyc}(G, F) = E_{x \sim p_{data}(x)} [\|F(G(x)) - x\|_1] + E_{y \sim p_{data}(y)} [\|G(F(y)) - y\|_1] \quad (22)$$

In these equations,  $p_{data}(x)$  and  $p_{data}(y)$  are the data distributions of the two input domains,  $X$  and  $Y$ ,

respectively.  $\lambda_{cyc}$  is a hyperparameter that regulates the relative significance of the cycle-consistency loss.

#### Other Variants

Beyond the previously discussed architectures, Larsen et al. [54] developed VAEGAN, which combines

Variational Autoencoders (VAE) and GAN. In this architecture, as shown in Figure 12, the encoder from the VAE processes existing data, and the encoded latent vectors are then used as input to the generator of the GAN, rather than random noise. This approach enables VAEGAN to synthesize high-quality data while operating in the latent variable space.

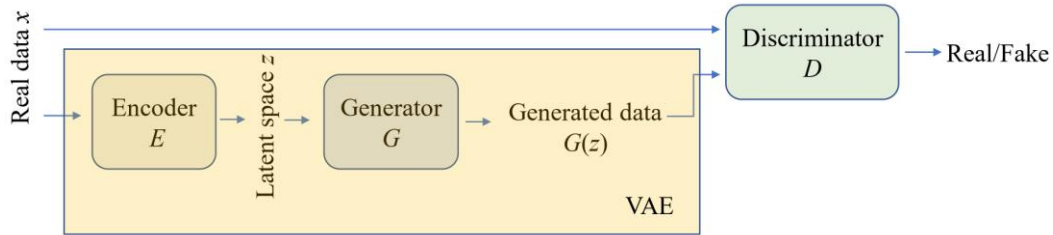


Figure 12. Structure of the VAEGAN.

Zhang et al. [55] presented an adaptive learning method for the latent vector input to the generator. Instead of sampling from a fixed Gaussian distribution, this adaptive input approach dynamically updates the

latent vector. This method has demonstrated improved performance, particularly in applications with limited training data. Figure 13 illustrates the structure of this adaptive input GAN.

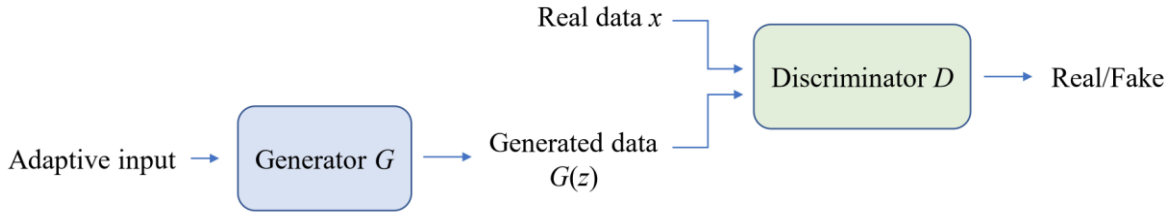


Figure 13. Structure of the adaptive input GAN.

Jolicoeur-Martineau [56] proposed the relativistic GAN (RGAN), which transforms the output of the discriminator into a measure of relative authenticity. This approach evaluates how much more realistic the discriminator perceives the fake data compared to the real data. The relative authenticity loss function has shown improved convergence and higher-quality image generation, addressing some of the stability issues in GAN training. Karras et al. [57] developed the progressive growing GAN (PGGAN), an innovative

method for synthesizing high-resolution images. PGGAN gradually increases the resolution of the generator and discriminator networks during the training process, starting from low resolutions and progressively scaling up. This strategy has proven highly effective in generating detailed, high-quality images. Another contribution from Karras et al. [58] is the StyleGAN, which disentangles the latent space into different factors of variation. This enables more intuitive and controllable image synthesis

These GAN variants demonstrate ongoing efforts to improve GAN performance and capabilities. For more detailed information on these and other GAN variants, readers are encouraged to refer to the broader literature in this field [20, 22, 59, 60]. The following

section presents the applications of these GAN variants in diagnosing faults in rotating machines.

#### Applications of GANs in Fault Diagnosis of Rotating Machines

This section reviews the applications of GANs in fault diagnosis for rotating machines, addressing the second research question (RQ2). The applications are categorized into four main areas: data augmentation, domain adaptation, transfer learning, and reconstructing missing accelerometric data.

#### *Applications of GANs in Data Augmentation*

A prominent application of GANs in fault diagnosis is data augmentation. This approach addresses small fault sample sizes and class imbalance issues, which are common in industrial settings.

#### *Standard GAN*

In the literature, numerous studies have demonstrated the effectiveness of using a standard GAN to generate synthetic fault data, whether as 2-D images or 1-D vibration signals. For instance, Li et al. [61] employed an adaptive training ratio approach with a standard GAN, which enhanced the training process and improved classification even with imbalanced data. This method also exhibited strong generalization

Zhang et al. [66] applied the standard GAN to expand the fault training samples for an attention-based feature fusion system, which enhanced the developed an improved GAN to produce fault data and then used this augmented data, which merges real and

applications. Zhang et al. [68] utilized the original GAN to generate synthetic vibration data, thereby expanding the training data in cases of imbalanced original data. The expanded training set was subsequently used to train a CNN for fault diagnosis.

The standard GAN architecture has proven effective for data augmentation; however, it may encounter limitations such as vanishing gradient issues, mode collapse, and difficulties in capturing complex temporal patterns in 1-D vibration signals. These challenges have prompted researchers to explore advanced GAN variants and architectures specifically designed for fault diagnosis in rotating equipment.

#### *Advanced GAN Variants in Data Augmentation*

To address the limitations of the standard GAN architecture, researchers have explored various advanced GAN variants. One such variant is the Wasserstein GAN (WGAN), which has been widely adopted for fault diagnosis data augmentation. The WGAN architecture substitutes the traditional GAN discriminator with a Wasserstein distance-based critic, resulting in more stable training and enhanced convergence. This metric alleviates the vanishing gradient problem and improves the generator's ability

capabilities when applied to diverse mechanical fault data. Mao et al. [62] devised a method for addressing imbalanced fault diagnosis in rolling bearings by integrating a GAN with a Stacked Denoising Autoencoder (SDAE). In this approach, the GAN generates synthetic samples of the minority class, while the SDAE extracts discriminative features for effective fault classification. Similarly, Zhong et al. [63] proposed an imbalanced bearing fault diagnosis scheme that utilizes a residual factorized hierarchical search-based GAN to enhance continuous wavelet transform time-frequency images.

Additionally, researchers have developed standard GAN-based methods to leverage the feature information in raw 1-D vibration signals. Luo et al. [64] presented a GAN model based on music theory knowledge to synthesize synthetic fault samples for early fault diagnosis of motor bearings. Liu et al. [65] introduced a GAN-based fault diagnosis system that utilizes fused multi-sensor 1-D data to generate synthetic data and improve the classification of rotating machinery.

generalization of deep CNN-based diagnosis for bearings. Furthermore, Liu et al. [67]

GAN-generated fault samples, to train a deep neural network-based fault classifier for wind turbine

to produce a broader range of synthetic data, thereby reducing the risk of mode collapse. Consequently, several studies have effectively utilized the WGAN for data augmentation in fault diagnosis applications. Fu et al. [69] employed a fused attention-guided WGAN to tackle the challenges linked with incomplete information from a single sensor and the shortage of multi-sensor fault samples. This approach merges real and augmented samples to train a residual CNN for effective fault diagnosis. Similarly, Wang et al. [70] used a WGAN to generate artificial vibration signals, and real and WGAN-generated vibration data were combined to train stacked autoencoders, which increased training data diversity and enhanced diagnostic accuracy compared with relying solely on limited real data.

Although the WGAN can address some limitations of the standard GAN, it may still face optimization challenges due to the application of weight clipping to enforce the Lipschitz constraint on the discriminator. To address this challenge, WGAN-GP has been used in several studies to generate synthetic fault samples. For instance, Zhang et al. [71] utilized WGAN-GP to produce synthetic fault samples, combining the real and WGAN-GP generated samples to train a deep 1-D CNN for fault diagnosis of rolling bearings. Luo et al. [72] developed a

WGAN-GP sampling strategy to create realistic synthetic vibration samples, leveraging this augmented dataset to train a 1-D CNN for rolling bearing fault diagnosis. Zhang et al. [73] employed a WGAN-GP to synthesize bearing fault vibration data, training a deep CNN-based diagnosis model that achieved high diagnostic accuracy even with small sample sizes. Moreover, Gao et al. [74] proposed a data augmentation strategy using WGAN-GP to generate synthetic data that supplemented the low-data input set for fault diagnosis, enhancing accuracy compared to methods without data augmentation. Yu et al. [75] presented a parallel classification WGAN-GP framework for bearing fault sample augmentation, using a Pearson loss to generate high-quality faulty bearing samples from healthy inputs and gradually balancing the imbalanced dataset. In [76], a WGAN meta-learning-based approach was proposed for early motor bearing fault detection, effectively addressing small sample sizes and data imbalance issues in early fault diagnosis. Koenig et al. [77] introduced a WGAN-GP-based data augmentation method that utilizes transient, time-dependent vibration data to synthetically expand the training set used to train a CNN-K-means model. In the study [82], a 1-D deep convolutional GAN was constructed to generate small sample size fault samples, thereby expanding the dataset for improved fault diagnosis of rotating machinery. Gao et al. [83] presented an integrated convolutional transformer GAN to generate high-quality synthetic data for rolling bearing fault diagnosis under limited data conditions. Han et al. [84] developed a deep adversarial CNN that employs adversarial learning as a regularization method to address overfitting with limited fault data. Similarly, Viola et al. [85] used a DCGAN-based generative model to produce synthetic samples, which were then used to train a CNN for ball bearing fault detection. Xie and Zhang [86] also utilized a DCGAN to generate new samples for minority classes in the fault diagnosis of rolling bearings. Zhang et al. [87] employed a DCGAN to augment the fault samples of permanent magnet motors, followed by the use of a residual connected CNN for enhanced fault classification. Oh and Jeong [88] used a DCGAN to tackle data imbalance in ball bearing fault diagnosis. A lightweight CNN was trained on the augmented dataset, which included real and synthetic fault samples, resulting in improved fault diagnosis accuracy.

Studies have successfully employed conditional GAN (cGAN) to tackle challenges in this domain. Unlike traditional GANs, which can only generate samples for a single fault class, cGANs utilize conditional inputs to produce multi-class fault samples. This capability has led to the generation of diverse synthetic fault data,

for bearing fault diagnosis. Tian et al. [78] developed a bidirectional WGAN-GP-based semi-supervised fault diagnosis system, applied to bearing and gearbox fault data with limited labeled data, achieving improved fault diagnosis performance. These advancements in WGAN-based methods demonstrate the effectiveness of the Wasserstein distance metric in overcoming the limitations of standard GAN and enhancing the accuracy of fault diagnosis systems.

Researchers have utilized another variant of GAN, known as DCGAN, to effectively learn and synthesize high-resolution, realistic vibration data for fault diagnosis. Several studies have demonstrated the efficacy of this approach. For example, Gao et al. [79] used a DCGAN to generate high-quality synthetic time-frequency feature images, which were then employed to train an adaptive deep CNN for fault classification. Chen et al. [80] developed a DCGAN-based method for automatically establishing thresholds to reliably detect anomalies in wind turbine generator bearings. Wang et al. [81] utilized a 1-D CNN-based DCGAN to generate synthetic faulty vibration data, which was subsequently

augmenting limited real-world datasets and significantly enhancing performance in fault classification. For instance, Wang et al. [89] adopted a combined cGAN-stacked autoencoder (cGAN-SAE) approach, where the cGAN generated multi-class fault vibration samples using category labels as conditional information. These generated samples were used for training the SAE in fault classification, demonstrating effectiveness in small sample scenarios. Similarly, Yang et al. [90] employed a cGAN to learn the distribution of real sample data and generate new 2-D fault image samples for bearing fault diagnosis. Pan et al. [91] introduced a cGAN-based feature generation network to synthesize 1-D feature sets containing abundant fault information, which helped overcome class imbalance for improved faulty detection. Zheng et al. [92] proposed a dual discriminator cGAN framework that produced higher quality synthetic frequency spectrum datasets compared to standard cGAN approaches. This augmented dataset was then utilized to train effective imbalanced fault diagnosis models, addressing the challenges posed by limited and imbalanced fault data.

Advances have combined the strengths of the conditional GAN (cGAN) and Deep Convolutional GAN (DCGAN), leading to the development of the c-DCGAN architecture (see Figure 14). The c-DCGAN approach, as proposed by Luo et al. [93], integrates the conditional input of the cGAN with the deep convolutional structure of the DCGAN. This integration enables the generation of high-quality, multi-class fault samples with

enhanced feature representation, addressing the challenges of data scarcity and class imbalance. Peng et al. [94] also proposed a fault diagnosis method for rolling bearings based on the c-DCGAN to expand 1-D vibration data, which effectively addressed the issue of imbalanced data and enhanced the fault classification ability of rolling bearings. Advancements have also been made by incorporating WGAN-GP into the cGAN framework. Li et al. [95] introduced a cWGAN-GP data generation approach that combines a cGAN and WGAN-GP to generate high-quality synthetic samples for bearing fault diagnosis under imbalanced data conditions. The generated samples were then used to train a gated recurrent unit for fault classification.

Similarly, Fu et al. [96] combined switchable normalization with cWGAN-GP, which effectively boosted the generalization ability of the diagnosis model. Furthermore, Gensheng and Jingquan [97] presented a lightweight cGAN-based method for small sample fault diagnosis, overcoming the limitations of complex CNN in existing studies [90, 93]. This method generated high-quality multi-class fault samples, significantly improving the diagnostic performance in bearing and gearbox case studies. These developments demonstrate the ongoing evolution and refinement of cGAN-based approaches in addressing challenges related to fault data scarcity and class imbalance in the field.

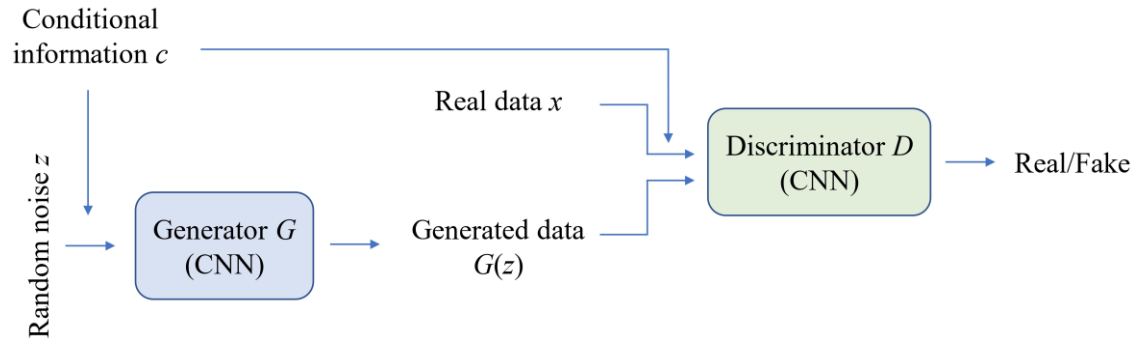


Figure 14. Structure of the c-DCGAN.

As an extension of the cGAN, the InfoGAN has been applied to fault diagnosis applications. Wu et al. [98] utilized semi-supervised InfoGAN to generate synthetic enables a DCNN to learn fault features more effectively, improving classification accuracy despite class imbalance. Verstraete et al. [99] applied InfoGAN in the fault diagnosis of bearings using time-frequency images. He et al. [100] developed a bidirectional InfoMax GAN to generate diverse latent features, augmenting limited data for effective fault diagnosis. This approach demonstrated rapid and efficient feature extraction and fault recognition, even with a limited number of samples.

Another extension of the cGAN, the auxiliary classifier GAN (ACGAN), has also been used for fault diagnosis.

fault samples for underrepresented classes, which were then used to enhance the training dataset. This

The ACGAN aims to generate high-quality fault data and has shown promising results in multi-class classification tasks. For instance, Li et al. [101] proposed an improved ACGAN model with enhanced synergy between the classification and discrimination components, efficiently generating high-quality multimode fault vibration samples. Shao et al. [102] employed the ACGAN framework to produce 1-D vibration data samples, which helped improve the fault diagnosis accuracy for motor systems. The specific data augmentation strategy used in this study is illustrated in Figure 15.

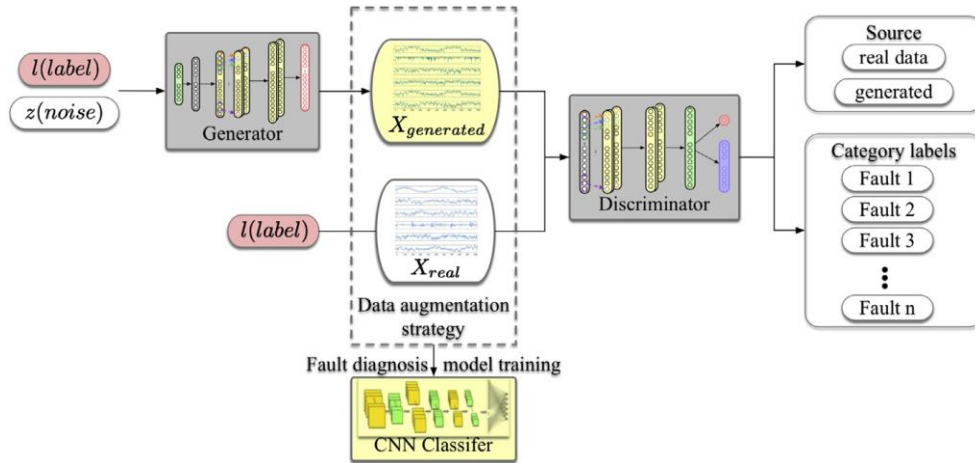


Figure 15. The ACGAN-based data augmentation strategy utilized in Shao et al. [102].

Recognizing the potential of 2-D representations, Huang et al. [103] developed a robust ACGAN architecture that processes samples in 2-D matrix format, incorporating mini-batch training and regularized mutual information for wind turbine fault diagnosis. Chen et al. [104] explored ACWGAN-GP-based models to generate 2-D grayscale images from 1-D time-domain vibration signals. Li et al. [105] also used ACWGAN-GP to produce 2-D frequency spectrum samples. To achieve direct 1-D vibration signal generation, Guo et al. [106] applied the ACGAN to generate synthetic fault data, which, when combined with real data, improved accuracy in bearing fault diagnosis. Likewise, Cao et al. [107] integrated ACWGAN-GP with an isomorphic stacked integrated learning method to enhance data augmentation and facilitate fault diagnosis in rotating machinery. To further improve the quality of the generated samples, Fu et al. [108] developed a feature-enhanced ACGAN that achieved impressive accuracy in diagnosing bearing faults. Luo et al. [109] presented a two-stage GAN framework (i.e., time-series GAN and ACGAN) to generate diverse, multimodal fault samples, which were then utilized to improve a wavelet-ResNet18 diagnosis model.

Building on previous applications of GAN-based data augmentation approaches, researchers have further investigated using semi-supervised GAN (SSGAN) for fault diagnosis. Wu et al. [110] and Liang et al. [111] utilized wavelet transforms to convert 1-D vibration signals into 2-D time-frequency images, which were subsequently used to train SSGAN models. This method facilitates the generation of high-quality synthetic fault data, enhancing diagnostic performance even when labeled samples are scarce. Additionally, researchers have explored alternative signal processing techniques alongside SSGANs. Li and Zhang

[112] introduced an SSGAN-based approach that leverages the fast Fourier transform to augment spectrum signals. This approach significantly increased the amount of available training data, thereby improving the model's diagnostic performance. To further refine SSGAN performance, Zhao et al. [113] integrated switchable normalization, which yielded positive results on experimental datasets. Xu and Wang [114] developed an SSGAN variant that incorporates spectral normalization. This approach efficiently utilizes partially labeled samples to generate synthetic data that closely mimics real-world fault signatures. Zhang et al. [115] also presented a semi-supervised fault diagnosis system that relies on feature extraction and an enhanced GAN.

The VAEGAN architecture has also shown notable promise in generating high-quality synthetic vibration data to complement limited real-world datasets. Rathore et al. [116] employed VAEGAN to produce time-frequency spectrograms, effectively balancing bearing fault datasets and enhancing sample quality. Zhang et al. [117] presented a multifaceted method that combines wavelet transforms, CVAE-GAN, and multisource signal fusion. This innovative method converts 1-D vibration signals into 2-D images, enabling the generation of class-specific vibration samples for diagnosing faults in wind turbines. Further refinements to the VAEGAN architecture have been introduced to improve fault diagnosis. Liu et al. [118] incorporated deep regret theory to enhance feature extraction and diagnostic capabilities, while their subsequent work [119] introduced a conditional VAEGAN with self-modulation, improving the diversity and quality of synthetic data. To address noisy vibration signals, Wang et al. [120] developed a patch-variant AEGAN, which demonstrated robust feature extraction abilities in comparative studies. Recognizing the susceptibility of

signals to faults and disturbances, Hong and Kim [121] proposed a dual approach: utilizing a 1-D CNN for signal monitoring and a VAEGAN for generating realistic fault samples. This method exhibited the capacity to capture complex system dynamics, advancing the field's diagnostic capabilities.

In addition to VAEGAN, researchers have explored various GAN variants to tackle specific challenges in vibration-based fault diagnosis. Yang et al. [122] integrated the EBGAN with the ACGAN to address imbalanced data conditions in bearing fault diagnosis, achieving notable success in both sample generation and classification tasks. Luo et al. [123] introduced an unsupervised enhanced RGAN, leveraging its strengths to synthesize high-quality synthetic data and improve diagnostic accuracy. In pursuit of more efficient training methods, Akhenia et al. [124] demonstrated the potential of single-image GANs, which require only one image for learning, in contrast with traditional GANs, which necessitate large datasets. This approach shows promise for sample-efficient training in fault diagnosis applications. Zhang et al. [55] further advanced the field with a multi-module GAN utilizing adaptive learning methods to update potential vectors, enhancing the model's capability to synthesize representative synthetic data. These diverse GAN variants have collectively expanded the toolbox available to researchers and practitioners.

Another significant development is the integration of meta-learning techniques with GANs to enhance model generalizability across various fault classes [130]. Dixit et al. [131] incorporated meta-learning into a conditional ACGAN to supplement the limited training data of air compressors, effectively addressing class imbalance issues. This approach allows the model to learn from multiple tasks or datasets, boosting its capacity to generate realistic samples for underrepresented fault classes.

Few-shot and zero-shot learning techniques have also shown promise in scenarios with extremely limited fault samples. Li et al. [132] explored parameter fine-tuning and a conditional WGAN to diagnose faults in freight train rolling bearings using few-shot learning. Ren et al. [133] presented a few-shot GAN to synthesize data with distributions similar to those of the original data. Chen et al. [134] employed a Wasserstein DCGAN to enhance few-shot fault diagnosis in electro-hydrostatic actuators. Expanding on this concept, Maggio et al. [135] developed a generative zero-shot learning method using CycleGAN for fault classification, thereby enabling the synthesis of realistic training data for previously unseen fault types.

### *Integration of GANs with Other Techniques*

Some studies have explored attention mechanisms combined with GANs to enhance data augmentation capabilities for fault diagnosis. One such example is the study of Fan et al. [125], who integrated a full-attention mechanism with WGAN to tackle imbalanced data, employing augmented data with a shallow 1-D CNN for accurate diagnosis. Gu et al. [126] presented a cosine similarity-based self-attention WGAN-GP to generate new frequency domain vibration samples, addressing imbalanced faulty data. Shang et al. [127] developed a self-attention WGAN-GP to expand the training samples for fault diagnosis and introduced a convolutional variational autoencoder to screen high-quality data, which increased diagnostic accuracy. In a related effort, Wan et al. [128] designed a rapid self-attentive convolutional GAN for bearing fault diagnosis, which proved effective even when labeled data was scarce. Huang et al. [129] presented a DCGAN-based approach that incorporates a gradient penalty, Wasserstein distance, self-attention, and spectral normalization. This comprehensive model generates high-quality synthetic fault samples, addressing both data scarcity and imbalance issues. These attention-enhanced GANs have shown the potential to improve the quality of generated samples by concentrating on the most informative features in vibration data, thus enhancing fault diagnosis performance.

### *Applications of GANs in Domain Adaptation*

Domain adaptation in fault diagnosis is crucial for addressing the discrepancies between training and deployment environments. These variations, which often arise from different operating conditions, sensor placements, or machine configurations, can significantly impair the performance of fault diagnosis models when applied to new target domains. Consequently, researchers have developed GAN-based domain adaptation strategies that generate synthetic vibration data to effectively bridge the source and target domains. Li et al. [136] pioneered this field with a GAN-based cross-domain fault diagnosis system for bearings under varying operating conditions. Alabsi et al. [137] also introduced a semi-supervised domain adaptation method that combines model optimization with a GAN to enhance the efficacy of cross-domain fault diagnosis.

However, the instability of standard GANs, such as gradient vanishing—where the generator receives very small gradients due to a strong discriminator and mode collapse, where the generator produces only a few types of outputs, can negatively affect the effectiveness of domain adaptation tasks. As a result,

researchers have turned to more advanced GAN variants to tackle these issues. Zhu et al. [138] and Sun et al. [139] applied WGAN to balance source-target distributions in bearing fault diagnosis and to augment the spectral data of hydroelectric units, respectively. Fan et al. [140] also utilized WGAN to address gradient vanishing and explosion issues during training. In a related study [141], WGAN-GP was used to recover fault features in rotating machinery health monitoring systems with missing data. Li and He [142] utilized this architecture to learn interpretable representations of gear parameters using limited data, whereas Liu et al. [143] developed it to enhance the diversity of synthesized data for better fault diagnosis. The least squares GAN architecture was employed in [144] to augment limited target domain fault data and train a domain adaptive group CNN for fault diagnosis under different loads.

Researchers have developed methods to enhance the quality and diversity of generated data. Ren et al. [145] introduced a GAN driven by multi-domain information along with a self-reasoning training strategy. Meanwhile, Chen et al. [146] advanced this method to improve fault diagnosis performance under unseen working conditions through domain augmentation and adversarial training.

To effectively manage the specific characteristics of industrial data, researchers have integrated GAN architectures with time-series models. Du et al. [147] developed an enhanced unsupervised LSTM-GAN model for real-time industrial signals. Similarly, Shen and Zha [148] utilized LSTM-GAN to generate high-quality time-series data from aircraft hydraulic systems. To tackle the challenge of limited labeled data, Xia et al. [149] introduced an augmentation-based discriminative meta-learning approach for addressing few-shot cross-machine domain shift issues. This method combines signal transformation and multi-scale learning for effective feature extraction.

#### *Applications of GANs in Transfer Learning Tasks*

Generative Adversarial Networks (GANs) have revolutionized transfer learning in fault diagnosis, addressing critical challenges such as limited data availability and class imbalance. This approach leverages knowledge from related equipment to enhance diagnostic capabilities for target machinery. One of the early contributions was by Guo et al. [150], who presented diagnosis methods based on adversarial learning for fault diagnosis across various bearings. This pioneering work laid the foundation for transfer learning under changing working conditions. Researchers have introduced various GAN-based

methods to tackle specific challenges in fault diagnosis. For instance, Zheng et al. [151] combined a multi-scale PGGAN with transfer learning to generate fault samples at multiple scales, while He et al. [152] utilized GANs to effectively address the issues of limited samples and fluctuations in data distribution across a range of operating conditions.

To combat data scarcity and class imbalance, Li et al. [153] developed a novel method based on temporal GAN and transfer learning. Liu et al. [154] introduced a conditional variational GAN for generating missing data under various operating conditions. Drawing inspiration from StyleGAN, Wang et al. [155] created a technique that generates samples aligned with the target domain distribution using incremental learning. Researchers have also emphasized optimizing GAN architectures for transfer learning. Peng et al. [156] improved the discriminator and employed parameter transfer learning to diagnose faults with limited labeled samples. Pei et al. [157] combined WGAN-GP with transfer learning for diagnosing faults in rolling bearings under different conditions to facilitate data transfer between the source and target domains.

GAN-based methods are highly effective in facilitating knowledge transfer across different domains or operating conditions. Cycle-GAN has gained popularity in this context, as Xie et al. [158] and Jiao et al. [159] have used it for bearing fault diagnosis and feature similarity assurance. Liu et al. [160] also employed Cycle-GAN to generate 1-D faulty samples from cross-domain bearing datasets. Similarly, Zhao et al. [161, 162] utilized Cycle-GAN for cross-condition data supplementation in fault diagnosis.

Furthermore, scholars have combined attention mechanisms and developed advanced architectures to enhance the effectiveness of GAN-based transfer learning. Zhao et al. [163] developed a multi-scale adversarial method with attention to gearbox fault diagnosis. Deng et al. [164] proposed a dual-layer attention-based GAN for various transfer tasks in fault diagnosis. These attention-based approaches enable models to focus on the most relevant features during the transfer learning process.

To resolve computational constraints, Zhong et al. [165] presented a knowledge distillation GAN integrated with Deep Transfer Learning (DTL) to reduce generation time and enable efficient fault diagnosis. This approach addresses the computational overhead often linked with GAN-based methods while preserving their benefits in transfer learning scenarios. Additionally, a

fault diagnosis system based on a GAN and DTL was introduced in [166] to tackle the computational overhead frequently encountered in GAN-based approaches. Recognizing the challenges of model interpretability in fault diagnosis, Brito et al. [167] developed a method utilizing transfer learning from enhanced synthetic data to actual machinery, balancing diagnostic accuracy with model transparency.

#### *Applications of GANs for Reconstructing Missing Accelerometric Vibration Data*

The reconstruction of missing accelerometric data presents a significant challenge in fault diagnosis, particularly in the context of rotating machinery. GANs are effective for this purpose, as these models learn the underlying distribution of available data and generate synthetic samples that closely resemble real signals. This process not only fills the gaps caused by data loss due to sensor failures or environmental factors but also enhances the overall robustness of diagnostic models.

Some studies have demonstrated the effectiveness of GANs in this domain. For instance, one study [168] presented an intelligent fault diagnosis method that combines a dynamic simulation model with WGAN-GP to reconstruct missing fault-type samples. Another study [169] proposed an Autoencoder-GAN (AE-GAN) specifically designed to reconstruct missing bearing vibration data. Results indicated that the AE-GAN outperformed traditional methods in terms of repair accuracy and convergence speed, while also enhancing the stability of GAN training through the integration of an autoencoder. In [76], WGAN was employed to reconstruct missing vibration data in motor bearing fault diagnosis, addressing issues related to small sample sizes and weak feature extraction. This approach significantly improved the accuracy of early fault detection in rotating machines, although the quality of early bearing vibration signals was not fully considered.

Moreover, Xie et al. [158] utilized a cycle-consistent GAN to generate new sample data, addressing the challenge of missing data in the fault diagnosis of rotating machinery. This method improved transfer learning by approximating distribution functions across various working conditions. A novel anomaly detection model for rotating machinery was also proposed in the study [170], which utilized data reconstruction with GANs alongside vibration energy features. This model achieved effective anomaly detection without requiring fault samples, attaining an impressive accuracy of 98.90% under different working conditions. Collectively, these studies demonstrate that the

application of GANs in reconstructing missing accelerometric data represents a significant advancement in fault diagnosis, offering viable solutions to the challenges posed by incomplete datasets.

#### *Quality Evaluation Metrics for GAN-Generated Vibration Data*

Following the detailed analysis of GAN applications in fault diagnosis, this section reviews the quality evaluation metrics and addresses the third research question (RQ3).

#### Evaluation Metrics

##### Metrics for 1-D Vibration Signals

To evaluate the similarity between GAN-generated vibration data and original data, researchers have implemented a range of evaluation metrics to effectively gauge the quality of the generated samples. Basic time-domain statistical characteristics such as mean, standard deviation, kurtosis, and skewness can be utilized to compare the quality of synthetic and real signals [102, 171, 172]. However, these metrics may not capture more complex temporal dynamics.

To address this limitation, the Pearson correlation coefficient (PCC) is often used to compute the linear relationship between synthesized data  $G(z)$  and original vibration data  $x$  [173]. Li et al. [95] utilized the PCC as a screening criterion to ensure the quality of fake data. The PCC can be calculated as:

$$PCC = \frac{\sum((G(z) - \overline{G(z)})(x - \bar{x}))}{\sqrt{\sum(G(z) - \overline{G(z)})^2 \sum(x - \bar{x})^2}} \quad (23)$$

Here,  $\overline{G(z)}$  and  $\bar{x}$  are the means of  $G(z)$  and  $x$ , respectively.

To complement time-domain analyses, researchers have also focused on frequency-domain characteristics. Spectral similarity metrics, such as the Spectral Angle Mapper (SAM) and spectral information divergence (SID), are utilized to compare the frequency content of the generated and real data. The SAM, which quantifies the similarity between the frequency content of the synthetic data and the real vibration data, can be expressed as [174]:

$$SAM = \arccos\left(\frac{S(G(z)) \cdot S(x)}{\|S(G(z))\| \|S(x)\|}\right) \quad (24)$$

where  $\|\cdot\|$  is a norm function and  $S(G(z))$  and  $S(x)$  are the spectral vectors of  $G(z)$  and  $x$ , respectively.

The SID can be adapted to compare the spectral probability distributions of generated and real data, which can be expressed as [175]:

$$SID = \sum pG(z)(f) \log\left(\frac{pG(z)(f)}{px(f)}\right) + \sum px(f) \log\left(\frac{px(f)}{pG(z)(f)}\right) \quad (25)$$

where  $pG(z)(f)$  and  $px(f)$  are the probability distributions of the spectral components for  $G(z)$  and  $x$ , respectively.

#### Metrics for 2-D Vibration Images

When GAN models generate 2-D vibration data, the evaluation metrics shift to those commonly used in image quality assessment. One widely used metric is the inception score (IS), which assesses both the quality and diversity of the generated data by measuring the Kullback-Leibler (KL) divergence between the conditional and marginal class probability distributions [176]. The IS can be mathematically expressed as:

$$IS = \exp\left(E_{x \sim p_g}[D_{KL}(p(y|x) || p(y))]\right) \quad (26)$$

Here,  $x \sim p_g$  signifies that  $x$  is an image sampled from  $p_g$ ,  $p(y|x)$  represents the conditional class probability distribution, and  $p(y)$  is the marginal class probability distribution.

To provide more distribution-level comparisons, researchers often employ the Maximum Mean Discrepancy (MMD) metric [152]. MMD calculates the distance between the mean embeddings of the synthesized and original data in a reproducing kernel Hilbert space, which can be expressed as [177]:

$$MMD = \left\| \overline{G(z)} - \bar{x} \right\|^2 \quad (27)$$

where  $\overline{G(z)}$  and  $\bar{x}$  represent the mean embeddings of the synthesized and original vibration images, respectively.

The Fréchet inception distance (FID) builds upon the concept of the inception score, comparing synthesized and original vibration images by computing the Fréchet distance between their feature representations [178]. For instance, Huang et al. [129] applied the FID metric to assess the quality of generated vibration samples generated via the DCGAN-based method. The FID can be mathematically expressed as [179]:

$$FID = \left\| \overline{G(z)} - \bar{x} \right\|^2 + T_r(\Sigma G(z) + \Sigma x - 2\sqrt{\Sigma G(z)\Sigma x}) \quad (28)$$

where  $\overline{G(z)}$ ,  $\Sigma G(z)$  and  $\bar{x}$ ,  $\Sigma x$  are the mean and covariance of the feature representations of the synthesized and original images, respectively.

For a more detailed distribution-level comparison, the Sliced Wasserstein Distance (SWD), which can be expressed as [180], is also frequently employed:

$$SWD = E[W_1(PG(z), Px)] \quad (29)$$

where  $W_1$  is the 1-D Wasserstein distance, and  $PG(z)$  and  $Px$  are the projections of the generated and real images, respectively.

#### Diversity Metrics

Diversity metrics are essential for evaluating the variability of generated samples and ensuring that GANs capture a wide range of scenarios. This is particularly important in fault diagnosis, where representing diverse fault scenarios can enhance model training. One diversity metric is pairwise distance, which calculates the pairwise distances between generated samples and averages these distances using measures such as Euclidean distance [95]. The average diversity score (ADS) can be expressed as:

$$ADS = \frac{1}{N(N-1)} \sum_{i=1}^N \sum_{j \neq i} d(x_i, x_j) \quad (30)$$

where  $d(x_i, x_j)$  is the distance between samples  $x_i$  and  $x_j$ , and  $N$  is the number of generated data.

Another diversity index is the Shannon entropy, which considers the distributions of various classes or features within the generated samples. The Shannon entropy ( $H$ ) can be calculated as [181]:

$$H = -\sum_{i=1}^k p_i \log(p_i) \quad (31)$$

where  $p_i$  is the proportion of samples belonging to class  $i$ , and  $k$  is the number of classes.

If the generated samples have multiple features, feature variability can be calculated by determining the variance of each feature across the samples. The average variability across features can serve as a diversity score, which can be calculated as:

$$ADS = \frac{1}{m} \sum_{j=1}^m Var(x_j) \quad (32)$$

where  $m$  is the number of features and  $Var(x_j)$  is the variance of feature  $j$ .

## Mode Coverage

In the context of GAN-generated data, particularly for fault diagnosis applications, mode coverage evaluates how well the generated data represent the various modes present in the real data distribution. This metric is crucial for identifying underrepresented fault types, as high mode coverage indicates that the GAN can effectively synthesize samples from different fault classes.

Mode density estimation is a mode coverage metric that evaluates the density of synthesized samples relative to the density of real samples across various fault classes. A higher density indicates better mode coverage [182]. The kernel density estimation can be calculated as:

$$Density(x) = \frac{1}{N} \sum_{i=1}^N K\left(\frac{x-x_i}{h}\right) \quad (33)$$

Here,  $k$  is the kernel function,  $h$  is the bandwidth, and  $x_i$  represents the samples.

Kullback-Leibler divergence can be utilized to measure how the distribution of synthesized samples diverges from the distribution of original samples across modes. This metrics can be expressed as [177]:

$$D_{KL}(P||Q) = \sum_i P(i) \log\left(\frac{P(i)}{Q(i)}\right) \quad (34)$$

where  $P$  is the distribution of original samples and  $Q$  is the distribution of generated samples.

The Mode Coverage Score (MCS) can be calculated based on the number of samples generated from each class relative to the total number of samples for that class in the real data [183]. The MCS can be expressed as:

$$MCS = \frac{1}{C} \sum_{c=1}^C \frac{n_{c\_generated}}{n_{c\_real}} \quad (35)$$

where  $C$  is the total number of classes,  $n_{c\_generated}$  is the number of generated samples from class  $c$ , and  $n_{c\_real}$  is the number of real samples from class  $c$ .

To this end, the review reveals that various metrics are available for assessing the quality, authenticity, similarity, and diversity of GAN-synthesized vibration data. To guide researchers and practitioners in selecting the appropriate evaluation methods, Table 2 presents a comprehensive overview of these metrics, along with defined thresholds that classify data quality as usable, good, or excellent. This guidance will

facilitate the selection of the most suitable evaluation strategies for specific needs.

Table 2. Comparative analysis of evaluation metrics for GAN-generated vibration data.

Metric	Advantages	Disadvantages	Usable quality threshold	Good quality threshold	Excellent quality threshold
PCC	Easy to compute  Straightforward measure of linear relationship	Only captures linear correlations  Sensitive to outliers	$PCC \geq 0.5$	$PCC \geq 0.7$	$PCC \geq 0.9$
SAM	Captures frequency domain characteristics  Robust against phase and amplitude differences	Sensitive to spectral parameters may not adequately capture time-domain features	$SAM \leq 0.1$ radians	$SAM \leq 0.05$ radians	$SAM \leq 0.01$ radians
SID	Compares spectral probability distributions	May not accurately capture time-domain features	$SID \leq 0.5$	$SID \leq 0.3$	$SID \leq 0.1$
IS	Evaluates quality and diversity  Leverages pretrained model capabilities	Computationally expensive  May not be optimized for vibration data	$IS \geq 2$	$IS \geq 3$	$IS \geq 4$
MMD	Distribution-level comparison  Can capture more complex statistical differences	Requires the selection of an appropriate kernel function	$MMD \leq 0.1$	$MMD \leq 0.05$	$MMD \leq 0.01$
FID	Captures both quality and diversity  Robust against mode collapse	Requires a pretrained model  May not be optimized for vibration features	$FID \leq 50$	$FID \leq 30$	$FID \leq 10$
SWD	Robust distribution-level comparison  Captures both local and global features	Computationally intensive  Requires the selection of projection directions	$SWD \leq 0.5$	$SWD \leq 0.3$	$SWD \leq 0.1$
Diversity metrics	Assesses variability within generated samples	May need extra computation	Average diversity score $\leq 0.6$	Average diversity score $\leq 0.8$	Average diversity score $\geq 0.9$

	Ensures broader representation of data	Diversity metrics thresholds need to be defined						
Mode coverage	Evaluates the representation of different modes in the data	May not fully capture all nuances of data distribution.	Covers 50% of modes	of	Covers 70% of modes	of	Covers 90% of modes	

### Impact of Synthetic Data Quality on Fault Diagnosis Performance

Recent studies have achieved significant improvements in fault diagnosis model performance with the incorporation of GAN-generated vibration data. For instance, Lu et al. [184] reported substantial enhancements in classification accuracy and the F1-score when synthetic data were integrated with real datasets. Similarly, Xie and Zhang [86] employed a DCGAN to synthesize additional samples for minority fault classes, improving diagnostic accuracy for underrepresented fault types.

Furthermore, Dong et al. [5] presented GAN-based data augmentation techniques that utilize compressed sensing for bearing fault diagnosis. The approach emphasized the diversity and fidelity of the generated data. Shao et al. [102] further developed an ACGAN-based method for generating realistic 1-D data from mechanical sensor signals, resulting in consistently higher accuracy in fault pattern detection. Li et al. [153] confirmed the utility of GAN-

generated data in transfer learning scenarios, achieving increased diagnostic accuracy during domain adaptation tasks.

### Practical Considerations and Ongoing Research Challenges

This section reviews the practical considerations and ongoing challenges of incorporating GAN-generated vibration data into real-world fault diagnosis workflows in order to address the fourth research question (**Error! Reference source not found.**).

#### Practical Considerations

As industries increasingly embrace advanced data-driven approaches, integrating synthetic data generated by GANs with real data has become essential for enhancing intelligent fault diagnosis systems. The deployment of GAN-generated vibration data plays a pivotal role in this process. Figure 16 illustrates the steps involved in incorporating GAN-generated vibration data into practical fault diagnosis workflows.

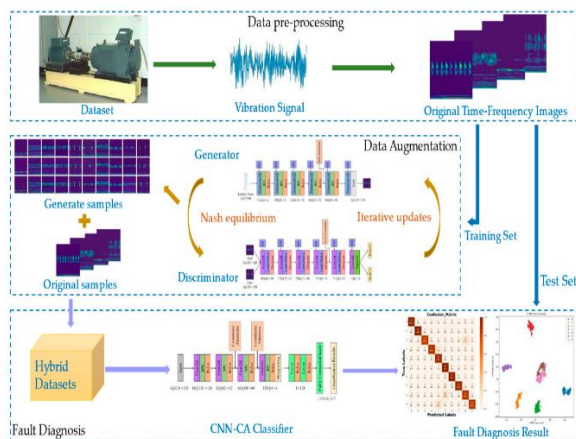


Figure 16. Steps for integrating GAN-generated vibration data into fault diagnosis workflows [129].

However, some critical practical considerations must be addressed to effectively implement these systems in real-world industrial applications. One crucial aspect of using GAN-based synthetic vibration data in industrial applications is regulatory compliance and standards. Adherence to industry regulations is vital, especially in sectors such as manufacturing, aerospace, and energy, where safety is paramount. Thus, organizations must establish comprehensive documentation and validation protocols to ensure the reliability of models utilizing synthetic data. Compliance with standards set by regulatory bodies, such as the ISO and IEEE, mitigates legal risks and fosters trust with stakeholders, including regulatory authorities and end users. In addition, protecting sensitive industrial data is essential, particularly when synthetic data may resemble proprietary

information. Therefore, organizations must implement robust data privacy measures to address the risks associated with data breaches. Techniques such as differential privacy and secure multiparty computation can help safeguard sensitive information while enabling effective data utilization. More importantly, ethical considerations surrounding data privacy are increasingly significant in the era of big data and artificial intelligence. It is crucial to address potential ethical concerns related to the use of synthetic data in safety-critical fault diagnosis applications. Therefore, prioritizing the development of privacy-preserving GAN architectures to protect sensitive information in industrial datasets is essential. The work of Jordon et al. [185] on PATE-GAN provides a promising approach for generating synthetic data while preserving privacy.

The compatibility between GAN-generated data and existing datasets and diagnosis models is another consideration for effective implementation in missing data while preserving dataset integrity, as discussed by Little and Rubin <sup>[186]</sup>. Approaches like PGGAN and StyleGAN can enhance control over the characteristics of generated vibration signals. This process involves aligning the format, structure, and statistical properties of both generated and real data. Furthermore, the successful integration of GAN-generated data into existing fault diagnosis workflows requires a comprehensive assessment of the technological infrastructure. For example, incorporating k-fold cross-validation for datasets augmented with GAN-generated samples ensures robust model evaluation, which is crucial for effective deployment in existing fault diagnosis systems <sup>[187]</sup>. This process validates the performance of models trained on hybrid datasets.

When generating fake data, it is essential to consider the characteristics of actual vibration sensors used in the field, such as sampling rates, frequency ranges, and noise profiles. Adjusting GAN architectures to reflect these parameters ensures that the generated data accurately mirror real-world scenarios, which enhances the reliability of fault diagnosis models. For example, if an industrial setting uses vibration sensors with specific sampling rates and frequency ranges, the GAN must be trained to produce data within these constraints. This alignment helps ensure that the fake data match the real-world limitations and capabilities of field monitoring equipment. Ignoring these characteristics can lead to discrepancies that undermine the performance of fault diagnosis systems.

In practical scenarios, domain experts play a vital role in the design, evaluation, and validation of GAN-generated data to enhance the relevance and reliability of synthetic outputs. User-friendly interfaces that incorporate familiar visualization tools facilitate the interaction and interpretation of synthetic data, which boosts acceptance and ensures alignment with operational needs and industry standards. To improve model interpretability, Lundberg and Lee <sup>[188]</sup> introduced SHapley Additive exPlanations (SHAP), which can be adapted to explain decisions in fault diagnosis models trained on GAN-generated data. Similarly, Bau et al. <sup>[173]</sup> worked on GAN dissection to enhance interpretability. The deployment of these diagnostic models benefits from continuous learning strategies, such as the online learning algorithms proposed by Sahoo et al. <sup>[189]</sup>, which enable models to update with new data. Organizations can also address potential distribution shifts between synthetic and real-world vibration data through domain-adversarial training, as suggested by Ganin et al. <sup>[190]</sup>. The integration of these strategies can enhance model performance

practical scenarios. Techniques such as normalization, scaling, and imputation help address

and ensure that insights derived from synthetic data are actionable and relevant to real-world applications.

Industrial applications often require substantial computational resources for training and deploying GANs, which can create barriers in resource-constrained environments. To address this challenge, GAN models need to be designed for efficient operation within existing infrastructure, thereby minimizing latency in data generation tasks. Scalability is also vital for handling varying data loads and operational contexts, particularly in high-demand scenarios. This may involve optimizing algorithms or leveraging cloud-based solutions that dynamically allocate resources as necessary. Furthermore, investigating model compression techniques and hardware-specific optimizations can enhance the feasibility of GAN deployment. Recent work by Han et al. <sup>[191]</sup> on efficient deep learning model compression presents promising strategies that could be tailored for GAN models in fault diagnosis applications.

Other practical considerations include assessing data quality, the necessity for comprehensive training datasets, establishing clear communication channels between technical teams and domain experts, and evaluating the cost-effectiveness of implementing GAN-generated data solutions. Collectively, these considerations ensure the successful integration of synthetic data into fault diagnosis systems and enhance overall effectiveness in meeting industrial demands.

### Ongoing Research Challenges

Although GAN variants for generating vibration data in the fault diagnosis of rotating machines show significant promise, challenges persist. One major issue is the complexity of fault signatures, as current GAN models often struggle to capture the full diversity of real-world fault patterns. Advanced techniques, such as transformer architectures, could enhance the modeling of long-range dependencies in vibration signals. For instance, the work of Vaswani et al. <sup>[192]</sup> on transformer architectures in natural language processing could be adapted for vibration signal generation. Another unresolved challenge is the robustness and reliability of generated data, particularly when confronted with noise, sensor degradation, and other real-world factors. To strengthen the resilience of GAN-generated samples, it is crucial to explore adversarial training techniques. The work of Madry et al. <sup>[193]</sup> on adversarial robustness offers valuable insights that can be

utilized to enhance the reliability of GAN-generated vibration data.

Furthermore, existing fault diagnosis models often struggle with new fault classes that have limited data samples. Although some studies, such as those by Wang et al. [194] have attempted to use GANs to augment samples from these new fault classes; however, more research is necessary to develop effective solutions for handling rare or previously unseen fault types. Finally, the continuous learning and adaptation of GAN models as new real-world data become available presents another important challenge. Therefore, it is essential to develop techniques that detect and mitigate potential degradation in GAN performance over time to maintain the long-term reliability of these systems. The concept of lifelong learning in artificial intelligence, as discussed by Chen and Liu [195], can be adapted for the continuous updating of GAN models in fault diagnosis applications.

By tackling these ongoing challenges, researchers and practitioners can more effectively integrate GAN-generated synthetic vibration data into fault diagnosis workflows. This integration ultimately enhances the reliability, adaptability, and performance of critical industrial applications.

#### *Recent Advancements and Future Research Directions*

This section presents recent research developments in GANs for vibration-based fault diagnosis and summarizes future research avenues to address the fifth research question (**Error! Reference source not found.**).

#### *Recent Developments*

As presented in the detailed analysis, the applications of the latest GAN variants, such as the relativistic GAN, CycleGAN, and progressive GAN, signify substantial progress in the field of synthetic vibration data generation for fault diagnosis in rotating machines. The integration of GANs with techniques such as attention mechanisms, transfer learning, meta-learning, few-shot learning, and zero-shot learning marks another key advancement in the field. These approaches improve GANs' capability to generalize from limited data and adapt to new fault scenarios.

Additionally, to better capture temporal dynamics and dependencies within vibration signals, researchers have made advancements by incorporating recurrent neural networks [196, 197] and transformer-based architectures into GAN models [198, 199]. As a result, these advancements produce synthetic vibration data with enhanced temporal coherence and patterns, which are crucial for

accurate fault diagnosis. Furthermore, researchers have examined the development of hierarchical or multi-scale GAN architectures capable of generating synthetic vibration data at varying levels of complexity and detail [200]. This flexibility addresses different use cases within the fault diagnosis pipeline, allowing for more efficient and targeted data augmentation to meet the diverse needs of diagnosis models and applications.

Moreover, advancements are being made in designing GAN models that can adaptively generate synthetic vibration data in real-time. This capability enables ongoing data augmentation and timely updates for fault diagnosis. Reinforcement learning has been incorporated to allow GAN models to update efficiently and adapt to evolving data and diagnostic requirements [201]. Researchers are also improving GAN architectures for vibration data synthesis by integrating fault mechanism models and introducing physically interpretable regularization terms in the loss function [202]. This approach enables the generated synthetic data to more accurately reflect physical fault characteristics and generation processes.

#### *Future Research Directions*

Although GAN-based synthetic vibration data generation enhances the fault diagnosis of rotating machines, further advancements are necessary in this evolving field. To this end, the following future research directions are proposed based on a detailed review. The first research direction involves the development of robust GAN architectures capable of generating diverse and representative synthetic vibration data for various practical fault scenarios. These architectures should be designed to tackle practical challenges, such as noisy, incomplete, or domain-shifted data, which occur in real-world situations while maintaining the effectiveness of these models for fault diagnosis under diverse working conditions. Another important research direction is the integration of explainable AI (xAI) with standard GAN and its variants. This integration can provide valuable insights into the fake data generation process and the physical significance of the generated fake data [203]. Thus, xAI-GAN is an emerging field of research that holds promise for improving the interpretability and trustworthiness of GAN-generated outputs.

Additionally, to reduce dependence on labeled fault data, new or improved GAN models that can learn useful representations from unlabeled vibration data are necessary. Unlabeled vibration data, which are not annotated or classified, is particularly valuable for GANs, as these models are designed to generate new data samples. Therefore, future research will shift towards integrating GANs with contrastive learning

approaches [204] and self-supervised pretraining techniques [205] to enhance the effectiveness of these models. Moreover, the exploration of hybrid data generation methods that combine GANs with other techniques, such as variational autoencoders or normalizing flows, can potentially lead to more robust and versatile synthetic data generation. For example, Brock et al. [206] introduced BigGAN, which demonstrated significant improvements in image quality and diversity. Similar hybrid approaches could be examined for vibration data generation.

Furthermore, recent advancements in Physics-Informed Neural Networks (PINNs) present promising opportunities for integrating domain knowledge into GAN architectures across various applications [207]. For instance, Raissi et al. [208] demonstrated the effectiveness of PINNs in solving both forward and inverse problems in fluid dynamics. This concept could be adapted to develop physics-informed GANs designed to generate vibration data in rotating machinery. In this context, Ge and Sadhu [45] proposed an unsupervised domain adaptation system for structural health monitoring that utilizes an adapted CycleGAN, incorporating physical constraints and a self-attention mechanism. By combining these approaches, future investigations could lead to more robust and accurate models for monitoring and predicting the behavior of complex mechanical systems.

Recent advancements in diffusion models have demonstrated remarkable results in generating high-quality synthetic data across various domains. Adapting these techniques to the vibration domain could lead to significant improvements in the quality of synthetic fault diagnosis data. The work on denoising diffusion probabilistic models by Ho et al. [209] in image generation provides a foundation that could be adapted for generating high-fidelity vibration signals.

Finally, methods for quantifying and improving the reliability of GAN-generated synthetic data must be developed. This involves creating comprehensive validation frameworks to ensure robustness against adversarial attacks and implementing techniques to detect and mitigate potential biases in the generated time-series data. By focusing on these research directions, the scientific community can make significant contributions to this evolving field.

## CONCLUSION

In this paper, we review the applications of Generative Adversarial Networks (GANs) and their variants in generating synthetic vibration data for fault diagnosis of rotating machines, particularly to address the challenges of small sample sizes and data imbalance. To this end, both comprehensive

and systematic approaches have been employed to analyze the current state of research in this field.

The fundamental structures and principles of standard GANs, along with recent advancements in GAN architectures, were explained. Building on this foundation, the applications of GANs in generating synthetic vibration data for fault diagnosis were examined in depth. This review specifically addresses four key applications of GANs in fault diagnosis: data augmentation, domain adaptation, transfer learning, and reconstructing missing accelerometric vibration data.

Additionally, the evaluation metrics for quality and diversity used to assess the generated vibration data are presented to ensure that the synthetic data meet the required standards for effective diagnostic applications. This paper also offers practical considerations and addresses ongoing research challenges in the field. Finally, future research directions in this rapidly evolving area are discussed. This review paper can guide researchers and practitioners, particularly maintenance and system design engineers, in exploring and developing GAN-based techniques for vibration-based fault diagnosis of rotating machines.

## Acknowledgments

This work was supported by the Artificial Intelligence and Robotics Center of Excellence at Addis Ababa Science and Technology University, [grant numbers IGP012/2023].

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## REFERENCES

1. Kibrete F, Woldemichael DE. Applications of artificial intelligence for fault diagnosis of rotating machines: A review. *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering (LNICST)*. Springer, Cham. 2023; 41–62. doi:10.1007/978-3-031-28725-1\_4
2. Kibrete F, Woldemichael DE, Gebremedhen HS. Multi-sensor data fusion in intelligent fault diagnosis of rotating machines: A comprehensive review. *Measurement*. 2024;114658. doi:10.1016/j.measurement.2024.114658
3. Romanssini M, de Aguirre PCC, Compassi-Severo L, Girardi AG. A review on vibration monitoring techniques for predictive maintenance of rotating machinery. *Eng*. 2023;4(3):102. doi:10.3390/eng4030102
4. Rahman A, Hoque ME, Rashid F, Alam F, Ahmed MM. Health condition monitoring and control of vibrations of a rotating system through vibration analysis. *Journal of Sensors*. 2022;2022:4281596. doi:10.1155/2022/4281596
5. Wang D, Dong Y, Wang H, Tang G. Limited fault data augmentation with compressed sensing for bearing fault diagnosis. *IEEE Sensors Journal*. 2023;23(13):14499–14511.

- doi:10.1109/JSEN.2023.3277563
6. Lundström A, O'Nils M. Factory-based vibration data for bearing-fault detection. *Data*. 2023;8(7):115. doi:10.3390/data8070115
  7. Martin-Diaz I, Morinigo-Sotelo D, Duque-Perez O, De Romero-Troncoso RJ. Early fault detection in induction motors using AdaBoost with imbalanced small data and optimized sampling. *IEEE Transactions on Industry Applications*. 2017;53(3):3066–3075. doi:10.1109/TIA.2016.2618756
  8. Zhang Y, Li X, Gao L, Wang L, Wen L. Imbalanced data fault diagnosis of rotating machinery using synthetic oversampling and feature learning. *Journal of Manufacturing Systems*. 2018;48:34–50. doi:10.1016/j.jmsy.2018.04.005
  9. Wei J, Huang H, Yao L, Hu Y, Fan Q, Huang D. New imbalanced bearing fault diagnosis method based on sample-characteristic oversampling technique (SCOTE) and multi-class LS-SVM. *Applied Soft Computing*. 2021;101:107043. doi:10.1016/j.asoc.2020.107043
  10. Zhang H, Li M. RWO-sampling: A random walk oversampling approach to imbalanced data classification. *Information Fusion*. 2014;20(1):99–116. doi:10.1016/j.inffus.2013.12.003
  11. Qian W, Li S, Yi P, Zhang K. A novel transfer learning method for robust fault diagnosis of rotating machines under variable working conditions. *Measurement*. 2019;138:514–525. doi:10.1016/j.measurement.2019.02.073
  12. Meng Z, Guo X, Pan Z, Sun D, Liu S. Data segmentation and augmentation methods based on raw data using deep neural networks approach for rotating machinery fault diagnosis. *IEEE Access*. 2019;7:79510–79522. doi:10.1109/ACCESS.2019.2923417
  13. Yu K, Lin TR, Ma H, Li X, Li X. A multi-stage semi-supervised learning approach for intelligent fault diagnosis of rolling bearing using data augmentation and metric learning. *Mechanical Systems and Signal Processing*. 2021;146:107043. doi:10.1016/j.ymsp.2020.107043
  14. Goodfellow IJ, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, et al. Generative adversarial networks. *arXiv preprint arXiv:1406.2661*. 2014.
  15. Lee YO, Jo J, Hwang J. Application of deep neural network and generative adversarial network to industrial maintenance: A case study of induction motor fault detection. In: *Proceedings of the 2017 IEEE International Conference on Big Data (Big Data 2017)*. IEEE; 2017. p. 3248–3253. doi:10.1109/BigData.2017.8258307
  16. Liu H, Zhou J, Xu Y, Zheng Y, Peng X, Jiang W. Unsupervised fault diagnosis of rolling bearings using a deep neural network based on generative adversarial networks. *Neurocomputing*. 2018;315:412–424. doi:10.1016/j.neucom.2018.07.034
  17. Wang Z, Wang J, Wang Y. An intelligent diagnosis scheme based on generative adversarial learning deep neural networks and its application to planetary gearbox fault pattern recognition. *Neurocomputing*. 2018;310:213–222. doi:10.1016/j.neucom.2018.05.024
  18. Zhao B, Yuan Q. Improved generative adversarial network for vibration-based fault diagnosis with imbalanced data. *Measurement*. 2021;169:108522. doi:10.1016/j.measurement.2020.108522
  19. Zareapoor M, Shamsolmoali P, Yang J. Oversampling adversarial network for class-imbalanced fault diagnosis. *Mechanical Systems and Signal Processing*. 2021;149:107175. doi:10.1016/j.ymsp.2020.107175
  20. Chakraborty T, Reddy KS U, Naik SM, Panja M, Manvitha B. Ten years of generative adversarial nets (GANs): A survey of the state-of-the-art. *Machine Learning: Science and Technology*. 2024. doi:10.1088/2632-2153/ad1f77
  21. Gonog L, Zhou Y. A review: Generative adversarial networks. In: *Proceedings of the 14th IEEE Conference on Industrial Electronics and Applications (ICIEA 2019)*. IEEE; 2019. p. 505–510. doi:10.1109/ICIEA.2019.8833686
  22. Gui J, Sun Z, Wen Y, Tao D, Ye J. A review on generative adversarial networks: Algorithms, theory, and applications. *IEEE Transactions on Knowledge and Data Engineering*. 2023;35(4):3313–3332. doi:10.1109/TKDE.2021.3130191
  23. Simion AM, Radu S, Florea AM. A review of generative adversarial networks for computer vision tasks. *Electronics*. 2024;13(4):713. doi:10.3390/electronics13040713
  24. Marano GC, Rosso MM, Aloisio A, Cirrincione G. Generative adversarial networks review in earthquake-related engineering fields. *Bulletin of Earthquake Engineering*. 2024;22(7):3511–3562. doi:10.1007/s10518-023-01645-7
  25. Jiang Y, Li J, Yang X, Yuan R. Applications of generative adversarial networks in materials science. *Materials Genome Engineering Advances*. 2024;2(1):e30. doi:10.1002/mgea.30
  26. Li Q, Tang Y, Chu L. Generative adversarial networks for prognostic and health management of industrial systems: A review. *Expert Systems with Applications*. 2024;124341. doi:10.1016/j.eswa.2024.124341
  27. Alqahtani H, Kavakli-Thorne M, Kumar G. Applications of generative adversarial networks (GANs): An updated review. *Archives of Computational Methods in Engineering*. 2021;28(2):525–552. doi:10.1007/s11831-019-09388-y
  28. Lee M. Recent advances in generative adversarial networks for gene expression data: A comprehensive review. *Mathematics*. 2023;11(14):3055. doi:10.3390/math11143055
  29. Trevisan de Souza VL, Marques BAD, Batagelo HC, Gois JP. A review on generative adversarial networks for image generation. *Computers & Graphics*. 2023;114:13–25. doi:10.1016/j.cag.2023.05.010
  30. Dash A, Ye J, Wang G. A review of generative adversarial networks (GANs) and its applications in a wide variety of disciplines: From medical to remote sensing. *IEEE Access*. 2024;12:18330–18357. doi:10.1109/ACCESS.2023.3346273
  31. Zhang T, et al. Intelligent fault diagnosis of machines with small and imbalanced data: A state-of-the-art review and possible extensions. *ISA Transactions*. 2022;119:152–171. doi:10.1016/j.isatra.2021.02.042
  32. Pan T, Chen J, Zhang T, Liu S, He S, Lv H. Generative adversarial network in mechanical fault diagnosis under small sample: A systematic review on applications and future perspectives. *ISA Transactions*. 2022;128:1–10. doi:10.1016/j.isatra.2021.11.040
  33. Ruan D, Chen X, Gühmann C, Yan J. Improvement of generative adversarial network and its application in bearing fault diagnosis: A review. *Lubricants*. 2023;11(2):74. doi:10.3390/lubricants11020074
  34. Liao W, Yang K, Fu W, Tan C, Chen B, Shan Y. A review: The application of generative adversarial network for mechanical fault diagnosis. *Measurement Science and Technology*. 2024. doi:10.1088/1361-6501/ad356d
  35. Lei Y, Yang B, Jiang X, Jia F, Li N, Nandi AK. Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical Systems*

- and Signal Processing. 2020;138:106587. doi:10.1016/j.ymsp.2019.106587
36. Guo Y, Zhang J, Sun B, Wang Y. Adversarial deep transfer learning in fault diagnosis: Progress, challenges, and future prospects. *Sensors*. 2023;23(16):7263. doi:10.3390/s23167263
  37. Badampudi D, Wohlin C, Petersen K. Experiences from using snowballing and database searches in systematic literature studies. In: *ACM International Conference Proceeding Series*. ACM; 2015. doi:10.1145/2745802.2745818
  38. Arjovsky M, Chintala S, Bottou L. Wasserstein GAN. *arXiv preprint arXiv:1701.07875*. 2017.
  39. Zhang Y, Ai Q, Xiao F, Hao R, Lu T. Typical wind power scenario generation for multiple wind farms using conditional improved Wasserstein generative adversarial network. *International Journal of Electrical Power & Energy Systems*. 2020;114:105388
  40. Gulrajani I, Ahmed F, Arjovsky M, Dumoulin V, Courville A. Improved training of Wasserstein GANs. In: *Advances in Neural Information Processing Systems*. 2017:5768–5778.
  41. Mao X, Li Q, Xie H, Lau RYK, Wang Z, Smolley SP. Least squares generative adversarial networks. In: *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*. IEEE; 2017. p. 2813–2821. doi:10.1109/ICCV.2017.304
  42. Radford A, Metz L, Chintala S. Unsupervised representation learning with deep convolutional generative adversarial networks. In: *Proceedings of the 4th International Conference on Learning Representations (ICLR 2016)*. 2016.
  43. Liu S, Wang H, Zhang X. Research on improved deep convolutional generative adversarial networks for insufficient samples of gas turbine rotor system fault diagnosis. *Applied Sciences*. 2022;12(7):3606. doi:10.3390/app12073606
  44. Mirza M, Osindero S. Conditional generative adversarial nets. *arXiv preprint arXiv:1411.1784*. 2014
  45. Ge L, Sadhu A. Domain adaptation for structural health monitoring via physics-informed and self-attention-enhanced generative adversarial learning. *Mechanical Systems and Signal Processing*. 2024;211:111236. doi:10.1016/j.ymsp.2024.111236
  46. Chen X, Duan Y, Houthoofd R, Schulman J, Sutskever I, Abbeel P. InfoGAN: Interpretable representation learning by information maximizing generative adversarial nets. In: *Advances in Neural Information Processing Systems*. 2016:2180–2188.
  47. Odena A, Olah C, Shlens J. Conditional image synthesis with auxiliary classifier GANs. In: *Proceedings of the 34th International Conference on Machine Learning (ICML 2017)*. 2017:4043–4055
  48. Salimans T, Goodfellow I, Zaremba W, Cheung V, Radford A, Chen X. Improved techniques for training GANs. In: *Advances in Neural Information Processing Systems*. 2016:2234–2242.
  49. Pasupa K, Tungjitnob S, Vatathanavaro S. Semi-supervised learning with deep convolutional generative adversarial networks for canine red blood cells morphology classification. *Multimedia Tools and Applications*. 2020;79(45–46):34209–34226. doi:10.1007/s11042-020-08767-z
  50. Zhao J, Mathieu M, LeCun Y. Energy-based generative adversarial network. In: *Advances in Neural Information Processing Systems*. 2016
  51. Berthelot D, Schumm T, Metz L. BEGAN: Boundary equilibrium generative adversarial networks. *arXiv preprint arXiv:1703.10717*. 2017.
  52. Zhu JY, Park T, Isola P, Efros AA. Unpaired image-to-image translation using cycle-consistent adversarial networks. In: *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*. IEEE; 2017. p. 2242–2251. doi:10.1109/ICCV.2017.244
  53. Huang W, Chen H, Zhao Q. Fault diagnosis of interturn fault in permanent magnet-synchronous motors based on cycle-generative adversarial networks and deep autoencoder. *Applied Sciences*. 2024;14(5):2139. doi:10.3390/app14052139
  54. Larsen ABL, Sønderby SK, Larochelle H, Winther O. Autoencoding beyond pixels using a learned similarity metric. In: *Proceedings of the 33rd International Conference on Machine Learning (ICML 2016)*. 2016. p. 2341–2349.
  55. Zhang K, Chen Q, Chen J, He S, Li F, Zhou Z. A multi-module generative adversarial network augmented with adaptive decoupling strategy for intelligent fault diagnosis of machines with small sample. *Knowledge-Based Systems*. 2022;239:107980. doi:10.1016/j.knsys.2021.107980
  56. Jolicoeur-Martineau A. The relativistic discriminator: A key element missing from standard GAN. In: *Proceedings of the 7th International Conference on Learning Representations (ICLR 2019)*. 2019.
  57. Karras T, Aila T, Laine S, Lehtinen J. Progressive growing of GANs for improved quality, stability, and variation. In: *Proceedings of the 6th International Conference on Learning Representations (ICLR 2018)*. 2018.
  58. Karras T, Laine S, Aila T. A style-based generator architecture for generative adversarial networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2021;43(12):4217–4228. doi:10.1109/TPAMI.2020.2970919
  59. Bhandari A, Tripathy B, Adate A, Saxena R, Gadekallu TR. From beginning to BEGANing: Role of adversarial learning in reshaping generative models. *Electronics*. 2023;12(1):155. doi:10.3390/electronics12010155
  60. Sharma P, Kumar M, Sharma HK, Biju SM. Generative adversarial networks (GANs): Introduction, taxonomy, variants, limitations, and applications. *Multimedia Tools and Applications*. 2024;1–48. doi:10.1007/s11042-024-18767-y
  61. Li Q, Chen L, Shen C, Yang B, Zhu Z. Enhanced generative adversarial networks for fault diagnosis of rotating machinery with imbalanced data. *Measurement Science and Technology*. 2019;30(11):115005. doi:10.1088/1361-6501/ab3072
  62. Mao W, Liu Y, Ding L, Li Y. Imbalanced fault diagnosis of rolling bearing based on generative adversarial network: A comparative study. *IEEE Access*. 2019;7:9515–9530. doi:10.1109/ACCESS.2018.2890693
  63. Zhong Z, Liu H, Mao W, Xie X, Hao W, Cui Y. Imbalanced bearing fault diagnosis based on RFH-GAN and PSA-DRSN. *IEEE Access*. 2023;11:131926–131938. doi:10.1109/ACCESS.2023.3335199
  64. Luo P, Yin Z, Yuan D, Gao F, Liu J. A novel generative adversarial networks via music theory knowledge for early fault intelligent diagnosis of motor bearings. *IEEE Transactions on Industrial Electronics*. 2024;71(8):9777–9788. doi:10.1109/TIE.2023.3321984
  65. Liu Q, Ma G, Cheng C. Data fusion generative adversarial network for multi-class imbalanced fault diagnosis of rotating machinery. *IEEE Access*. 2020;8:70111–70124. doi:10.1109/ACCESS.2020.2986356
  66. Zhang T, He S, Chen J, Pan T, Zhou Z. Toward small sample challenge in intelligent fault diagnosis: Attention-weighted multidepth feature fusion net with signals augmentation. *IEEE Transactions on Instrumentation and Measurement*. 2022;71. doi:10.1109/TIM.2021.3134999

67. Liu J, Qu F, Hong X, Zhang H. A small-sample wind turbine fault detection method with synthetic fault data using generative adversarial nets. *IEEE Transactions on Industrial Informatics*. 2019;15(7):3877–3888. doi:10.1109/TII.2018.2885365
68. Zhang W, Li X, Jia XD, Ma H, Luo Z, Li X. Machinery fault diagnosis with imbalanced data using deep generative adversarial networks. *Measurement*. 2020;152:107377. doi:10.1016/j.measurement.2019.107377
69. Fu W, Yang K, Wen B, Shan Y, Li S, Zheng B. Rotating machinery fault diagnosis with limited multisensor fusion samples by fused attention-guided Wasserstein GAN. *Symmetry*. 2024;16(3):285. doi:10.3390/sym16030285
70. Wang J, Li S, Han B, An Z, Bao H, Ji S. Generalization of deep neural networks for imbalanced fault classification of machinery using generative adversarial networks. *IEEE Access*. 2019;7:111168–111180. doi:10.1109/ACCESS.2019.2924003
71. Zhang H, Wang R, Pan R, Pan H. Imbalanced fault diagnosis of rolling bearing using enhanced generative adversarial networks. *IEEE Access*. 2020;8:185950–185963. doi:10.1109/ACCESS.2020.3030058
72. Luo J, Zhu L, Li Q, Liu D, Chen M. Imbalanced fault diagnosis of rotating machinery based on deep generative adversarial networks with gradient penalty. *Processes*. 2021;9(10):1751. doi:10.3390/pr9101751
73. Zhang T, Chen J, Li F, Pan T, He S. A small sample focused intelligent fault diagnosis scheme of machines via multimodules learning with gradient penalized generative adversarial networks. *IEEE Trans Ind Electron*. 2021;68(10):10130–10141. doi:10.1109/TIE.2020.3028821
74. Gao X, Deng F, Yue X. Data augmentation in fault diagnosis based on the Wasserstein generative adversarial network with gradient penalty. *Neurocomputing*. 2020;396:487–494. doi:10.1016/j.neucom.2018.10.109
75. Yu Y, Guo L, Gao H, Liu Y. PCWGAN-GP: A new method for imbalanced fault diagnosis of machines. *IEEE Trans Instrum Meas*. 2022;71. doi:10.1109/TIM.2022.3180431
76. Yu Y, Guo L, Gao H, Liu Y. PCWGAN-GP: A new method for imbalanced fault diagnosis of machines. *IEEE Trans Instrum Meas*. 2022;71. doi:10.1109/TIM.2022.3180431
77. Koenig T, Cadau L, Wagner F, Kley M. A generative adversarial network-based data augmentation approach with transient vibration data. *Procedia Comput Sci*. 2023;1340–1349. doi:10.1016/j.procs.2023.10.122
78. Cui L, Tian X, Shi X, Wang X, Cui Y. A semi-supervised fault diagnosis method based on improved bidirectional generative adversarial network. *Appl Sci*. 2021;11(20):9401. doi:10.3390/app11209401
79. Gao Y, Piltan F, Kim JM. A novel image-based diagnosis method using improved DCGAN for rotating machinery. *Sensors*. 2022;22(19):7534. doi:10.3390/s22197534
80. Chen P, Li Y, Wang K, Zuo MJ, Heyns PS, Baggeröhr S. A threshold self-setting condition monitoring scheme for wind turbine generator bearings based on deep convolutional generative adversarial networks. *Measurement*. 2020;167:108234. doi:10.1016/j.measurement.2020.108234
81. R. Wang, S. Zhang, Z. Chen, and W. Li, "Enhanced generative adversarial network for extremely imbalanced fault diagnosis of rotating machines," *Measurement*, vol. 180, p. 109467, Aug. 2021, doi: 10.1016/j.measurement.2021.109467.
82. W. Jiang, C. Wang, J. Zou, and S. Zhang, "Application of deep learning in fault diagnosis of rotating machinery," *Processes*, vol. 9, no. 6, p. 919, Jun. 2021, doi: 10.3390/pr9060919.
83. H. Gao, X. Zhang, X. Gao, F. Li, and H. Han, "ICoT-GAN: Integrated convolutional transformer GAN for rolling bearings fault diagnosis under limited data conditions," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, 2023, doi: 10.1109/TIM.2023.3271729.
84. T. Han, C. Liu, W. Yang, and D. Jiang, "A novel adversarial learning framework in deep convolutional neural networks for intelligent diagnosis of mechanical faults," *Knowledge-Based Systems*, vol. 165, pp. 474–487, Feb. 2019, doi: 10.1016/j.knsys.2018.12.019.
85. J. Viola, Y. Q. Chen, and J. Wang, "FaultFace: Deep convolutional generative adversarial network (DCGAN)-based ball-bearing failure detection method," *Information Sciences*, vol. 542, pp. 195–211, Jan. 2021, doi: 10.1016/j.ins.2020.06.060.
86. Y. Xie and T. Zhang, "Imbalanced learning for fault diagnosis of rotating machinery based on generative adversarial networks," in *Proceedings of the Chinese Control Conference (CCC)*, IEEE, Oct. 2018, pp. 6017–6022, doi: 10.23919/ChiCC.2018.848333
87. D. Zhang, Z. Q. Ning, B. Yang, T. Y. Wang, and Y. J. Ma, "Fault diagnosis of permanent magnet motors based on DCGAN-RCCNN," *Energy Reports*, vol. 8, pp. 616–626, Jul. 2022, doi: 10.1016/j.egy.2022.01.226.
88. J. W. Oh and J. Jeong, "Data augmentation for bearing fault detection with a lightweight CNN," *Procedia Computer Science*, vol. 176, pp. 72–79, Jan. 2020, doi: 10.1016/j.procs.2020.07.013
89. J. Wang, B. Han, H. Bao, M. Wang, Z. Chu, and Y. Shen, "Data augmentation method for machine fault diagnosis using conditional generative adversarial networks," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, Jun. 2020, doi: 10.1177/0954407020923258.
90. J. Yang, J. Liu, J. Xie, C. Wang, and T. Ding, "Conditional GAN and 2-D CNN for bearing fault diagnosis with small samples," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, 2021, doi: 10.1109/TIM.2021.3119135.
91. T. Pan, J. Chen, J. Xie, Z. Zhou, and S. He, "Deep feature generating network: A new method for intelligent fault detection of mechanical systems under class imbalance," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 9, pp. 6282–6293, Sep. 2021, doi: 10.1109/TII.2020.3030967
92. T. Zheng, L. Song, J. Wang, W. Teng, X. Xu, and C. Ma, "Data synthesis using dual-discriminator conditional generative adversarial networks for imbalanced fault diagnosis of rolling bearings," *Measurement*, vol. 158, p. 107741, Jul. 2020, doi: 10.1016/j.measurement.2020.107741
93. J. Luo, J. Huang, and H. Li, "A case study of conditional deep convolutional generative adversarial networks in machine fault diagnosis," *Journal of Intelligent Manufacturing*, vol. 32, no. 2, pp. 407–425, Feb. 2021, doi: 10.1007/s10845-020-01579-w
94. C. Peng, S. Zhang, and C. Li, "Rolling bearing fault diagnosis based on conditional deep convolutional countermeasure generation networks under small samples," *Sensors*, vol. 22, no. 15, p. 5658, Jul. 2022, doi: 10.3390/s22155658
95. M. Li, D. Zou, S. Luo, Q. Zhou, L. Cao, and H. Liu, "A new generative adversarial network-based imbalanced fault diagnosis method," *Measurement*, vol. 194, p. 111045, May 2022, doi: 10.1016/j.measurement.2022.111045.

96. W. Fu, Y. Chen, H. Li, X. Chen, and B. Chen, "Imbalanced fault diagnosis using conditional Wasserstein generative adversarial networks with switchable normalization," *IEEE Sensors Journal*, vol. 23, no. 23, pp. 29119–29130, Dec. 2023, doi: 10.1109/JSEN.2023.3322040.
97. G. Qian and J. Liu, "Fault diagnosis based on conditional generative adversarial networks in nuclear power plants," *Annals of Nuclear Energy*, vol. 176, p. 109267, Oct. 2022, doi: 10.1016/j.anucene.2022.109267.
98. J. Wu, Z. Zhao, C. Sun, R. Yan, and X. Chen, "SS-InfoGAN for class-imbalance classification of bearing faults," *Procedia Manufacturing*, vol. 49, pp. 99–104, Jan. 2020, doi: 10.1016/j.promfg.2020.07.003.
99. D. B. Verstraete, E. L. Droguett, V. Meruane, M. Modarres, and A. Ferrada, "Deep semi-supervised generative adversarial fault diagnostics of rolling element bearings," *Structural Health Monitoring*, vol. 19, no. 2, pp. 390–411, May 2020, doi: 10.1177/1475921719850576.
100. S. Liu, J. Chen, S. He, E. Xu, H. Lv, and Z. Zhou, "Intelligent fault diagnosis under small sample size conditions via bidirectional InfoMax GAN with unsupervised representation learning," *Knowledge-Based Systems*, vol. 232, p. 107488, Nov. 2021, doi: 10.1016/j.knsys.2021.107488.
101. W. Li, X. Zhong, H. Shao, B. Cai, and X. Yang, "Multi-mode data augmentation and fault diagnosis of rotating machinery using modified ACGAN designed with a new framework," *Advanced Engineering Informatics*, vol. 52, p. 101552, Apr. 2022, doi: 10.1016/j.aei.2022.101552.
102. S. Shao, P. Wang, and R. Yan, "Generative adversarial networks for data augmentation in machine fault diagnosis," *Computers in Industry*, vol. 106, pp. 85–93, Apr. 2019, doi: 10.1016/j.compind.2019.01.001.
103. N. Huang, Q. Chen, G. Cai, D. Xu, L. Zhang, and W. Zhao, "Fault diagnosis of bearings in wind turbine gearboxes under actual operating conditions driven by limited data with noisy labels," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, 2021, doi: 10.1109/TIM.2020.3025396.
104. B. Chen, C. Tao, J. Tao, Y. Jiang, and P. Li, "Bearing fault diagnosis using ACWGAN-GP enhanced by principal component analysis," *Sustainability*, vol. 15, no. 10, p. 7836, May 2023, doi: 10.3390/su15107836.
105. Z. Li, T. Zheng, Y. Wang, Z. Cao, Z. Guo, and H. Fu, "A novel method for imbalanced fault diagnosis of rotating machinery based on generative adversarial networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, 2021, doi: 10.1109/TIM.2020.3009343.
106. Q. Guo, Y. Li, Y. Song, D. Wang, and W. Chen, "Intelligent fault diagnosis method based on full 1-D convolutional generative adversarial networks," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 3, pp. 2044–2053, Mar. 2020, doi: 10.1109/TII.2019.2934901.
107. Z. Cao, Z. Li, J. Zhang, and H. Fu, "A homogeneous stacking ensemble learning model for fault diagnosis of rotating machinery with small samples," *IEEE Sensors Journal*, vol. 22, no. 9, pp. 8944–8959, May 2022, doi: 10.1109/JSEN.2022.3163760.
108. W. Fu, X. Jiang, C. Tan, B. Li, and B. Chen, "Rolling bearing fault diagnosis in limited data scenarios using feature-enhanced generative adversarial networks," *IEEE Sensors Journal*, vol. 22, no. 9, pp. 8749–8759, May 2022, doi: 10.1109/JSEN.2022.3160762.
109. W. Luo et al., "Fault diagnosis method based on two-stage GAN for data imbalance," *IEEE Sensors Journal*, vol. 22, no. 22, pp. 21961–21973, Nov. 2022, doi: 10.1109/JSEN.2022.3211021.
110. P. Liang, C. Deng, J. Wu, Z. Yang, J. Zhu, and Z. Zhang, "Single and simultaneous fault diagnosis of gearboxes via a semi-supervised and high-accuracy adversarial learning framework," *Knowledge-Based Systems*, vol. 198, p. 105895, Jun. 2020, doi: 10.1016/j.knsys.2020.105895.
111. P. Liang, C. Deng, J. Wu, G. Li, Z. Yang, and Y. Wang, "Intelligent fault diagnosis via semi-supervised generative adversarial networks and wavelet transform," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 7, pp. 4659–4671, Jul. 2020, doi: 10.1109/TIM.2019.2956613.
112. X. Li and F. L. Zhang, "Classification of multi-type bearing fault features based on semi-supervised generative adversarial networks," *Measurement Science and Technology*, vol. 35, no. 2, p. 025107, Nov. 2024, doi: 10.1088/1361-6501/ad068e.
113. D. Zhao, F. Liu, and H. Meng, "Bearing fault diagnosis based on switchable normalization SSGAN with one-dimensional vibration signal representation," *Sensors*, vol. 19, no. 9, p. 2000, Apr. 2019, doi: 10.3390/s19092000.
114. M. Xu and Y. Wang, "An imbalanced fault diagnosis method for rolling bearings based on semi-supervised conditional generative adversarial networks with spectral normalization," *IEEE Access*, vol. 9, pp. 27736–27747, 2021, doi: 10.1109/ACCESS.2021.3058334.
115. L. Zhang, B. Wang, P. Liang, X. Yuan, and N. Li, "Semi-supervised fault diagnosis of gearboxes based on feature pre-extraction mechanisms and improved generative adversarial networks under limited labeled samples and noisy environments," *Advanced Engineering Informatics*, vol. 58, p. 102211, Oct. 2023, doi: 10.1016/j.aei.2023.102211.
116. M. S. Rathore and S. P. Harsha, "Nonlinear vibration response analysis of rolling bearings for data augmentation and characterization," *Journal of Vibration Engineering & Technology*, vol. 11, no. 5, pp. 2109–2131, Jul. 2023, doi: 10.1007/s42417-022-00691-w.
117. L. Zhang, H. Zhang, and G. Cai, "Multiclass fault diagnosis of wind turbine bearings based on multisource signal fusion and deep learning generative models," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, 2022, doi: 10.1109/TIM.2022.3178483.
118. S. Liu, H. Jiang, Z. Wu, and X. Li, "Rolling bearing fault diagnosis using variational autoencoding generative adversarial networks with deep regret analysis," *Measurement*, vol. 168, p. 108371, Jan. 2021, doi: 10.1016/j.measurement.2020.108371.
119. Y. Liu, H. Jiang, Y. Wang, Z. Wu, and S. Liu, "Conditional variational autoencoding generative adversarial networks with self-modulation for rolling bearing fault diagnosis," *Measurement*, vol. 192, p. 110888, Mar. 2022, doi: 10.1016/j.measurement.2022.110888.
120. X. Wang, H. Jiang, Y. Liu, and Q. Yang, "Data-augmented patch variational autoencoding generative adversarial networks for rolling bearing fault diagnosis," *Measurement Science and Technology*, vol. 34, no. 5, p. 055102, Feb. 2023, doi: 10.1088/1361-6501/acb377.
121. D. Hong and B. Kim, "One-dimensional convolutional neural network-based adaptive algorithm structure with system fault diagnosis and signal feature extraction for noise and vibration enhancement in mechanical systems," *Mechanical Systems and Signal Processing*, vol. 197, p. 110395, Aug. 2023, doi: 10.1016/j.ymsp.2023.110395.

122. J. Yang, S. Yin, and T. Gao, "An efficient method for imbalanced fault diagnosis of rotating machinery," *Measurement Science and Technology*, vol. 32, no. 11, p. 115025, Aug. 2021, doi: 10.1088/1361-6501/ac18d2.
123. J. Luo, Y. Zhang, F. Yang, and X. Jing, "Imbalanced data fault diagnosis of rolling bearings using enhanced relative generative adversarial networks," *Journal of Mechanical Science and Technology*, vol. 38, no. 2, pp. 541–555, Feb. 2024, doi: 10.1007/s12206-024-0104-2.
124. P. Akhenia, K. Bhavsar, J. Panchal, and V. Vakharia, "Fault severity classification of ball bearings using SinGAN and deep convolutional neural networks," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, vol. 236, no. 7, pp. 3864–3877, Dec. 2022, doi: 10.1177/09544062211043132.
125. J. Fan, X. Yuan, Z. Miao, Z. Sun, X. Mei, and F. Zhou, "Full-attention Wasserstein GAN with gradient normalization for fault diagnosis under imbalanced data," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, 2022, doi: 10.1109/TIM.2022.3190525.
126. X. Gu, Y. Yu, L. Guo, H. Gao, and M. Luo, "CSWGAN-GP: A new method for bearing fault diagnosis under imbalanced conditions," *Measurement*, vol. 217, p. 113014, Aug. 2023, doi: 10.1016/j.measurement.2023.113014.
127. Z. Shang, J. Zhang, W. Li, S. Qian, J. Liu, and M. Gao, "A novel small-sample fault diagnosis method based on self-attention Wasserstein generative adversarial networks," *Neural Processing Letters*, vol. 55, no. 5, pp. 6377–6407, Oct. 2023, doi: 10.1007/s11063-022-11143-7.
128. W. Wan, S. He, J. Chen, A. Li, and Y. Feng, "QSCGAN: An unsupervised quick self-attention convolutional GAN for rolling element bearing fault diagnosis under limited unlabeled data," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, 2021, doi: 10.1109/TIM.2021.3125973.
129. Z. Qin, F. Huang, J. Pan, J. Niu, and H. Qin, "Improved generative adversarial networks for bearing fault diagnosis with small and imbalanced datasets," *Symmetry*, vol. 16, no. 3, p. 358, Mar. 2024, doi: 10.3390/sym16030358.
130. R. Wang, Z. Chen, and W. Li, "Gradient flow-based meta generative adversarial networks for data augmentation in fault diagnosis," *Applied Soft Computing*, 142, p. 110313, Jul. 2023, doi: 10.1016/j.asoc.2023.110313.
131. S. Dixit, N. K. Verma, and A. K. Ghosh, "Intelligent fault diagnosis of rotary machines: Conditional auxiliary classifier GAN coupled with meta-learning using limited data," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, 2021, doi: 10.1109/TIM.2021.3082264.
132. C. Li, K. Yang, H. Tang, P. Wang, J. Li, and Q. He, "Fault diagnosis for rolling bearings of freight trains under limited fault data using few-shot learning," *Journal of Transportation Engineering, Part A: Systems*, vol. 147, no. 8, p. 04021041, Jun. 2021, doi: 10.1061/jtepbs.0000554.
133. Z. Ren, Y. Zhu, Z. Liu, and K. Feng, "Few-shot GAN: Improving the performance of intelligent fault diagnosis in severe data imbalance," *IEEE Trans. Instrum. Meas.*, 72, 2023, doi: 10.1109/TIM.2023.3271746.
134. H. Chen, X. Miao, W. Mao, S. Zhao, G. Yang, and Y. Bo, "Fault diagnosis of EHA with few-shot data augmentation technique," *Smart Mater. Struct.*, vol. 32, no. 4, p. 044005, Mar. 2023, doi: 10.1088/1361-665X/acc0ed.
135. L. G. Di Maggio, E. Brusa, and C. Delprete, "Zero-shot generative AI for rotating machinery fault diagnosis: Synthesizing highly realistic training data via cycle-consistent adversarial networks," *Appl. Sci.*, 13, 22, p. 12458, Nov. 2023, doi: 10.3390/app132212458
136. Li X, Zhang W, Ding Q. Cross-domain fault diagnosis of rolling element bearings using deep generative neural networks. *IEEE Transactions on Industrial Electronics*. 2019;66(7):5525–5534.
137. Alabsi M, Pearlstein L, Franco-Garcia M. Cross domain fault diagnosis based on generative adversarial networks. *Journal of Vibration and Control*. 2023.
138. Zhu H, Huang Z, Lu B, Cheng F, Zhou C. Imbalance domain adaptation network with adversarial learning for fault diagnosis of rolling bearing. *Signal, Image and Video Processing*. 2022;16(8):2249–2257.
139. Sun W, Zou Y, Wang Y, Xiao B, Zhang H, Xiao Z. Fault diagnosis in hydroelectric units in small-sample state based on Wasserstein generative adversarial network. *Water*. 2024;16(3):454.
140. Hong-wei F, Ning-ge M, Xu-hui Z, Ce-yi X, Jia-teng M, Yang Y. New intelligent fault diagnosis approach of rolling bearing based on improved vibration gray texture image and vision transformer. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*. 2024;238(13):6117–6130.
141. Hu W, Wang T, Chu F. Fault feature recovery with Wasserstein generative adversarial imputation network with gradient penalty for rotating machine health monitoring under signal loss condition. *IEEE Transactions on Instrumentation and Measurement*. 2022;71.
142. Li J, He H. Information generative Bayesian adversarial networks: A representation learning model for transmission gear parameters. *IEEE/ASME Transactions on Mechatronics*. 2019;24(5):1998–2007
143. Liu S, Jiang H, Wu Z, Liu Y, Zhu K. Machine fault diagnosis with small sample based on variational information constrained generative adversarial network. *Advanced Engineering Informatics*. 2022;54:101762.
144. Li X, Yu T, He Q, Li D, Xie Z, Kong X. Domain adaptive networks with limited data for rotating machinery fault diagnosis: A case study of gears. *Measurement Science and Technology*. 2023;34(12):125123.
145. Ren Z, Gao D, Zhu Y, Ni Q, Yan K, Hong J. Generative adversarial networks driven by multi-domain information for improving the quality of generated samples in fault diagnosis. *Engineering Applications of Artificial Intelligence*. 2023;124:106542
146. Li Q, Chen L, Kong L, Wang D, Xia M, Shen C. Cross-domain augmentation diagnosis: An adversarial domain-augmented generalization method for fault diagnosis under unseen working conditions. *Reliability Engineering and System Safety*. 2023;234:109171.
147. Du W, Yang J, Meng G. Fault diagnosis for dynamic system based on the independent latent space reconstruction of generative adversarial network. *Journal of Process Control*. 2023;125:28–40.
148. Shen K, Zhao D. A fault diagnosis method under data imbalance based on generative adversarial network and long short-term memory algorithms for aircraft hydraulic system. *Aerospace*. 2023;10(2):164.
149. Xia PC, Huang YX, Wang YX, Liu CL, Liu J. Augmentation-based discriminative meta-learning for cross-machine few-shot fault diagnosis. *Science China Technological Sciences*. 2023;66(6):1698–1716.
150. Zhang R, Tao H, Wu L, Guan Y. Transfer learning with neural networks for bearing fault diagnosis in changing working conditions. *IEEE Access*.

- 2017;5:14347–14357.
151. Zheng M, Chang Q, Man J, Liu Y, Shen Y. Two-stage multi-scale fault diagnosis method for rolling bearings with imbalanced data. *Machines*. 2022;10(5):336.
  152. He W, Chen J, Zhou Y, Liu X, Chen B, Guo B. An intelligent machinery fault diagnosis method based on GAN and transfer learning under variable working conditions. *Sensors*. 2022;22(23):9175.
  153. Li J, Liu Y, Li Q. Generative adversarial network and transfer-learning-based fault detection for rotating machinery with imbalanced data condition. *Measurement Science and Technology*. 2022;33(4):045103.
  154. Liu X, Ma H, Liu Y. A novel transfer learning method based on conditional variational generative adversarial networks for fault diagnosis of wind turbine gearboxes under variable working conditions. *Sustainability*. 2022;14(9):5441.
  155. Wang Y, Zeng L, Ding X, Wang L, Shao Y. Incremental learning of bearing fault diagnosis via style-based generative adversarial network. *Proceedings of the International Conference on Sensing, Measurement and Data Analytics in the Era of Artificial Intelligence*. 2020:512–517.
  156. Peng C, Li L, Chen Q, Tang Z, Gui W, He J. A fault diagnosis method for rolling bearings based on parameter transfer learning under imbalance data sets. *Energies*. 2021;14(4):944.
  157. Pei X, Su S, Jiang L, Chu C, Gong L, Yuan Y. Research on rolling bearing fault diagnosis method based on generative adversarial and transfer learning. *Applied Sciences*. 2022;10(8):1443.
  158. Xie Y, Zhang T. A transfer learning strategy for rotation machinery fault diagnosis based on cycle-consistent generative adversarial networks. *Proceedings of the Chinese Automation Congress*. 2018:1309–1313.
  159. Jiao J, Lin J, Zhao M, Liang K, Ding C. Cycle-consistent adversarial adaptation network and its application to machine fault diagnosis. *Neural Networks*. 2022;145:331–341.
  160. Liu X, Liu S, Xiang J, Sun R. A transfer learning strategy based on numerical simulation driving 1D Cycle-GAN for bearing fault diagnosis. *Information Sciences*. 2023;642:119175.
  161. Zhao J, Huang W. Transfer learning method for rolling bearing fault diagnosis under different working conditions based on CycleGAN. *Measurement Science and Technology*. 2022;33(2):025003.
  162. Zhao B, Cheng C, Zhang G, Lin M, Peng Z, Meng G. An instance and feature-based hybrid transfer model for fault diagnosis of rotating machinery with different speeds. *IEEE Transactions on Instrumentation and Measurement*. 2022;71.
  163. Zhao B, Zhang X, Zhan Z, Wu Q. Deep multi-scale adversarial network with attention: A novel domain adaptation method for intelligent fault diagnosis. *Journal of Manufacturing Systems*. 2021;59:565–576.
  164. Deng Y, Huang D, Du S, Li G, Zhao C, Lv J. A double-layer attention based adversarial network for partial transfer learning in machinery fault diagnosis. *Computers in Industry*. 2021;127:103399.
  165. Zhong H, Yu S, Trinh H, Yuan R, Lv Y, Wang Y. A lightweight GAN-based fault diagnosis method based on knowledge distillation and deep transfer learning. *Measurement Science and Technology*. 2024;35(3):036103
  166. Zhong H, Yu S, Trinh H, Yuan R, Lv Y, Wang Y. A time-saving fault diagnosis using simplified fast GAN and triple-type data transfer learning. *Structural Health Monitoring*. 2024.
  167. Brito LC, Susto GA, Brito JN, Duarte MAV. Fault diagnosis using explainable AI: A transfer learning-based approach for rotating machinery exploiting augmented synthetic data. *Expert Systems with Applications*. 2023;232:120860.
  168. Ma J, Jiang X, Han B, Wang J, Zhang Z, Bao H. Dynamic simulation model-driven fault diagnosis method for bearing under missing fault-type samples. *Applied Sciences*. 2023;13(5):2857.
  169. Zhu Q, Zhang T, Fan G, Hao C, Fu G. Missing data repairing for bearing vibrations using generative adversarial networks. *ACM International Conference Proceeding Series*. 2022
  170. Li J, Liu Y, Wang Q, Xing Z, Zeng F. Rotating machinery anomaly detection using data reconstruction generative adversarial networks with vibration energy analysis. *AIP Advances*. 2022;12(3).
  171. Wang L, Li Q, Qin J. Rotating machinery fault diagnosis method based on improved semisupervised generative confrontation network. *Scientific Programming*. 2021;2021:1761446.
  172. Altaf M, Akram T, Khan MA, Iqbal M, Ch MMI, Hsu CH. A new statistical features based approach for bearing fault diagnosis using vibration signals. *Sensors*. 2022;22(5):2012.
  173. Tsialiamanis G, Champneys MD, Dervilis N, Wagg DJ, Worden K. On the application of generative adversarial networks for nonlinear modal analysis. *Mechanical Systems and Signal Processing*. 2022;166:108473.
  174. Zhan Y, Wang Y, Yu X. Semisupervised hyperspectral image classification based on generative adversarial networks and spectral angle distance. *Scientific Reports*. 2023;13(1):1–23.
  175. Xie W, Zhang J, Lei J, Li Y, Jia X. Self-spectral learning with GAN-based spectral-spatial target detection for hyperspectral image. *Neural Networks*. 2021;142:375–387.
  176. Barratt S, Sharma R. A note on the inception score. *arXiv*. 2018;arXiv:1801.01973.
  177. Jia Z, Yu B. A fault diagnosis method for rolling bearings of wind turbine generators based on MCGAN data enhancement. *SN Applied Sciences*. 2023;5(10):1–13.
  178. Lupo Pasini M, Yin J. Stable parallel training of Wasserstein conditional generative adversarial neural networks. *Journal of Supercomputing*. 2023;79(2):1856–1876.
  179. Heusel M, Ramsauer H, Unterthiner T, Nessler B, Hochreiter S. GANs trained by a two time-scale update rule converge to a local Nash equilibrium. *Advances in Neural Information Processing Systems*. 2017:6627–6638.
  180. Zhao K, Jiang H, Liu C, Wang Y, Zhu K. A new data generation approach with modified Wasserstein auto-encoder for rotating machinery fault diagnosis with limited fault data. *Knowledge-Based Systems*. 2022;238:107892
  181. Wang Z, Peng J, Sun Y. Bearing fault diagnosis based on novel hierarchical multiscale dispersion entropy in corresponding color block images. *Engineering Research Express*. 2024;6(4):045523.
  182. Mei J, Liu W, Zhu M, Qi Y, Xu W, Xu H. Class-relevant feature density estimator for open set fault classification of industrial equipment using vibration signals. *Measurement*. 2024;224:113806.
  183. Schreurs J, De Meulemeester H, Fanuel M, De Moor B, Suykens JAK. Leverage score sampling for complete mode coverage in generative adversarial networks. *Lecture Notes in Computer Science*. 2022:466–480.
  184. Shao L, Lu N, Jiang B, Simani S, Song L, Liu Z. Improved generative adversarial networks with filtering mechanism for fault data augmentation. *IEEE Sensors Journal*. 2023;23(13):15176–15187.

185. Jordon J, Yoon J, Van Der Schaar M. PATE-GAN: Generating synthetic data with differential privacy guarantees. Proceedings of the International Conference on Learning Representations. 2019.
186. Little RJA, Rubin DB. Statistical analysis with missing data. *Statistical Analysis with Missing Data*. 2019;1–449.
187. Guo J, Wang Y, Sun X, Liu S, Du B. Imbalanced data fault diagnosis method for nuclear power plants based on convolutional variational autoencoding Wasserstein generative adversarial network and random forest. *Nuclear Engineering and Technology*. 2024;56(12):5055–5067.
188. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*. 2017;4766–4775.
189. Sahoo D, Pham Q, Lu J, Hoi SCH. Online deep learning: Learning deep neural networks on the fly. Proceedings of the International Joint Conference on Artificial Intelligence. 2018;2660–2666.
190. Ganin Y, et al. Domain-adversarial training of neural networks. *Advances in Computer Vision and Pattern Recognition*. 2017;189–209.
191. Kibrete F, Woldemichael DE. Applications of artificial intelligence for fault diagnosis of rotating machines: A review. *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering*. 2023;41–62.
192. Kibrete F, Woldemichael DE, Gebremedhen HS. Multi-sensor data fusion in intelligent fault diagnosis of rotating machines: A comprehensive review. *Measurement*. 2024.
193. Romanssini M, de Aguirre PCC, Compassi-Severo L, Girardi AG. A review on vibration monitoring techniques for predictive maintenance of rotating machinery. *Engineering*. 2023;4(3):102.
194. Rahman A, Hoque ME, Rashid F, Alam F, Ahmed MM. Health condition monitoring and control of vibrations of a rotating system through vibration analysis. *Journal of Sensors*. 2022;2022:4281596.
195. Wang D, Dong Y, Wang H, Tang G. Limited fault data augmentation with compressed sensing for bearing fault diagnosis. *IEEE Sensors Journal*. 2023;23(13):14499–14511.
196. Lundström A, O’Nils M. Factory-based vibration data for bearing-fault detection. *Data*. 2023;8(7):115.
197. Martin-Diaz I, Morinigo-Sotelo D, Duque-Perez O, Romero-Troncoso RJD. Early fault detection in induction motors using AdaBoost with imbalanced small data and optimized sampling. *IEEE Transactions on Industry Applications*. 2017;53(3):3066–3075.
198. Zhang Y, Li X, Gao L, Wang L, Wen L. Imbalanced data fault diagnosis of rotating machinery using synthetic oversampling and feature learning. *Journal of Manufacturing Systems*. 2018;48:34–50.
199. Wei J, Huang H, Yao L, Hu Y, Fan Q, Huang D. New imbalanced bearing fault diagnosis method based on sample-characteristic oversampling technique and multi-class LS-SVM. *Applied Soft Computing*. 2021;101:107043.
200. Shen, Z., Kong, X., Cheng, L., Wang, R., & Zhu, Y. (2024). Fault diagnosis of the rolling bearing by a multi-task deep learning method based on a classifier generative adversarial network. *Sensors*, 24(4), 1290. <https://doi.org/10.3390/s24041290>.
201. Yan, K., Lu, C., Ma, X., Ji, Z., & Huang, J. (2024). Intelligent fault diagnosis for air handling units based on improved generative adversarial network and deep reinforcement learning. *Expert Systems with Applications*, 240, 122545. <https://doi.org/10.1016/j.eswa.2023.122545>
202. Zhou, K., Diehl, E., & Tang, J. (2023). Deep convolutional generative adversarial network with semi-supervised learning enabled physics elucidation for extended gear fault diagnosis under data limitations. *Mechanical Systems and Signal Processing*, 185, 109772. <https://doi.org/10.1016/j.ymssp.2022.109772>
203. Nagisetty, V., Graves, L., Scott, J., & Ganesh, V. (2020). xAI-GAN: Enhancing generative adversarial networks via explainable AI systems. Preprint.
204. Pöppelbaum, J., Chadha, G. S., & Schwung, A. (2022). Contrastive learning based self-supervised time-series analysis. *Applied Soft Computing*, 117, 108397. <https://doi.org/10.1016/j.asoc.2021.108397>
205. Zhang, K., et al. (2024). Self-supervised learning for time series analysis: Taxonomy, progress, and prospects. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. <https://doi.org/10.1109/TPAMI.2024.3387317>
206. Brock, A., Donahue, J., & Simonyan, K. (2019). Large-scale GAN training for high fidelity natural image synthesis. In Proceedings of the 7th International Conference on Learning Representations (ICLR 2019).
207. Kibrete, F., Woldemichael, D. E., & Gebremedhen, H. S. (2025). Hierarchical adaptive wavelet-guided adversarial network with physics-informed regularization for generating multiscale vibration signals for deep learning-based fault diagnosis of rotating machines. *Automation*, 6(2), 14. <https://doi.org/10.3390/automation6020014>
208. Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378, 686–707. <https://doi.org/10.1016/j.jcp.2018.10.045>
209. Ho, J., Jain, A., & Abbeel, P. (2020). Denoising diffusion probabilistic models. In *Advances in Neural Information Processing Systems*.