Digital twin-driven partial domain adaptation network for intelligent fault diagnosis of rolling bearing

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Abstract

Fault diagnosis of rolling bearings has attracted extensive attention in industrial fields, which plays a vital role in guaranteeing the reliability, safety, and economical efficiency of mechanical systems. Traditional data-driven fault diagnosis methods require obtaining a dataset of full failure modes in advance as the training data. However, this kind of dataset is not always available in some critical industrial scenarios, which impairs the practicability of the data-driven fault diagnosis methods for various applications. A digital twin, which establishes a virtual representation of a physical entity to mirror its operating conditions, would make fault diagnosis of rolling bearings feasible when the fault data are insufficient. In this paper, we propose a novel digital twin-driven approach for implementing fault diagnosis of rolling bearings with insufficient training data. First, a dynamics-based virtual representation of rolling bearings is built to generate simulated data. Then, a Transformer-based network is developed to learn the knowledge of the simulated data for diagnostics. Meanwhile, a selective adversarial strategy is introduced to achieve cross-domain feature alignments in scenarios where the health conditions of the measured data are unknown. To this end, this study proposes a digital twin-driven fault diagnosis framework by using labeled simulated data and unlabeled measured data. The experimental results show that the proposed method can obtain high diagnostic performance when the real-world data is unlabeled and has unknown health conditions, proving that the proposed method has significant benefits for the health management of critical rolling bearings.

Keywords: Digital twin, rolling bearing, fault diagnosis, domain adaptation, Transformer

1. Introduction

Rolling bearings are one of the important and crucial components in mechanical systems. In general, the bearings operate under harsh working conditions, making them prone to failure. A tiny failure on the bearing can significantly impair the overall performance of rotating machinery and even cause a sudden breakdown of the production process \cite{1,2,3}. Therefore, it is essential to diagnose the bearing failure to ensure its normal operation \cite{4,5,6,7}.

In recent years, deep learning technology has been continuously developed and successfully applied in the field of fault diagnosis \cite{8,9}. This type of technology can automatically evaluate the operating health conditions of mechanical equipment based on raw monitoring data. For example, Shao et al. \cite{10} presented a deep wavelet auto-encoder method based on the Gaussian wavelet function for bearing fault diagnosis. Mao et al. \cite{11} utilized...
the discriminant information on multiple fault types to develop a novel auto-encoder method for diagnosing bearing faults. Zhao et al. [12] proposed a remarkable intelligent fault diagnosis method based on the deep sparse auto-encoder, in which the local and nonlocal information were considered simultaneously. Liu et al. [13] presented a recurrent neural network-based autoencoder for bearing fault diagnosis, and used the information from multiple sensors to avoid the loss of local information and improve diagnostic performance. Zhao et al. [14] proposed a convolutional neural network (CNN) for fault diagnosis of the planet bearing by using the synchrosqueezing transform and Hilbert transform to obtain the representations of the vibration signals. Huang et al. [15] proposed a multi-scale cascade CNN for fault diagnosis, in which the multi-scale cascade layer was used to make different fault signals easier to distinguish. Wang et al. [16] established a multitask attention CNN method that could conduct fault identification and working conditions identification for rolling bearings. Plakias et al. [17] combined the dense convolutional blocks and the attention mechanism to develop a new attentive dense CNN for fault diagnosis. Although these methods can achieve high performance in fault diagnosis, the application of these methods is usually under the assumption that test data and training data come from the same data distribution. Unfortunately, this presumption seems unlikely in many industrial applications [18, 19]. As for bearings, their operating conditions, application scenarios, or environment noises are usually variable from one application to another [20]. The discrepancy in data distribution between training data and test data can result in a remarkable degeneration in the diagnosis performance [21]. Moreover, it is usually impractical to acquire sufficient supervised fault data under various application scenarios. This weakens the general applicability of these deep-learning techniques.

To solve the issue of data distribution discrepancy, various domain adaptation techniques based on transfer learning have been introduced for diagnosing bearing faults [22, 23, 24]. Domain adaptation techniques can transfer the diagnostic knowledge learned from the supervised source domain to the unsupervised target domain by learning invariant feature representations [25]. At present, cross-domain fault diagnosis is carried out by using maximum mean discrepancy (MMD), domain adversarial neural networks (DANN), or fusing two algorithms. For example, Lu et al. [26] proposed a cross-domain fault diagnosis method based on MMD loss, in which an MMD loss was used to measure the feature distance of the source domain and the target domain, and it was minimized during the training process to achieve the domain-invariant. Zhang et al. [27] established a cross-domain fault diagnosis method based on class-level alignment, in which the MMD loss and the supervised contrastive learning loss were trained simultaneously. Li et al. [28] developed a multi-kernel MMD cross-domain fault diagnosis method to further reduce the feature distribution discrepancy between the two domains. Han et al. [29] proposed a cross-domain fault diagnosis method based on DANN, in which a domain discriminator was added to achieve domain-invariant learning. Huang et al. [30] established a new deep adversarial capsule network to achieve the cross-domain fault diagnosis of the compound fault. Wu et al. [31] proposed a Gaussian-guided adversarial cross-domain fault diagnosis network for rolling bearings, in which the Gaussian-guided distribution alignment strategy was used to reduce the data distribution discrepancies of two domains. Zhang et al. [32] established a fusion cross-domain fault diagnosis method by combining MMD and DANN. Zhao et al. [33] developed a joint distribution adaptation network with adversarial learning, which was able to achieve precise distribution matching of the source domain and target domain. The role of domain adaptation learning in these methods is to derive domain-invariant feature representation across two domains. However, existing cross-domain fault diagnosis methods need to learn diagnosis knowledge from the source domain data, i.e., the source domain data should contain condition
monitoring data for all failure modes. This requirement is challenging to be met for some bearings used in critical scenarios where failures are not allowed. Therefore, existing domain adaptation methods are ineffective under insufficient source domain data.

Recently, with the development of technologies such as cyber-physical systems, industrial Internet of Things, and virtual reality, the concept of digital twin (DT) has received extensive attention in various fields of intelligent manufacturing, such as product design, job-shop scheduling, and process optimization [34]. DT is regarded as an effective tool to realize the interactive fusion of the cyber world and the physical world. High-fidelity digital models of physical entities can produce simulated data that approximate the performance of real systems. Therefore, DT is an emerging technology to address the scarcity of labeled data in real-world industrial scenarios and is gaining fast momentum in the field of machinery health management research [35]. A schematic diagram of machinery health management tasks based on the digital twin is shown in Fig 1. DT is a virtual mirror of a physical entity along its lifecycle. Through real-time interaction between the physical entity and the virtual model, the anomaly and fault status of the component and its remaining useful life (RUL) can be reflected and evaluated effectively. For instance, Xia et al. [36] developed a DT-assisted fault diagnosis method for the triplex pump, in which a simulation model of a real triplex pump was used to generate simulated fault data; and a sparse de-noising auto-encoder model based on fine-tuned was built to implement fault diagnosis. Liu et al. [37] proposed a DT model for predicting the RUL of the bearing, in which a phenomenological vibration model was introduced to generate simulated fault data, and a DANN was developed to achieve domain invariance of simulated data and measured data. Guo et al. [37] also proposed a DT model using the dynamic model for condition monitoring of rolling bearings. Qin et al. [38] developed an enhanced CycleGAN neural network for connecting the virtual world and the physical entity, and used it to evaluate the degradation conditions of bearings. Yu et al. [39] developed a simulation data-driven weakly supervised bearing cross-domain fault diagnosis method with insufficient label information. Based on a joint domain network, Xiao et al. [40] established a bearing cross-domain diagnosis method from simulated data to measured data. Wang et al. [41] proposed a novel DT-based diagnostic framework for rotor unbalance fault of rotating machinery, in which a parameter sensitivity analysis strategy was developed to improve the model adaptability. Zhang et al. [42] proposed a dynamic model-assisted RUL prediction method for rolling bearing. Feng et al. [43, 44, 45] conducted a series of research works in digital twin-based system degradation prediction, by utilizing modeling techniques and advanced vibration analysis. Later, Feng et al. [46] developed a practical digital frame and integrated it with transfer learning to achieve an accurate assessment of gearbox transmission degradation. Simulation-based DT has a great potential to reduce reliance on labeled measured data in the health management of mechanical components.

In the fault diagnosis field of rolling bearings, DT can generate simulated data for invisible fault conditions, providing new opportunities for realizing unsupervised fault diagnosis. However, some critical issues impede the digital twin techniques from being widely applied in bearing fault diagnosis. The first challenge is the establishment of a general high-fidelity digital twin model. There are many sizes, types, and operating conditions of rolling bearings. It is a time consuming and laborious process to establish a high-fidelity dynamic model for different bearings. Therefore, it is crucial to establish a general high-fidelity generalized bearing dynamic model, which includes the key features of the bearing system. The second challenge is the data distribution discrepancy between the simulated domain and the measured domain. Unlike DT-based RUL prediction tasks, fault diagnosis has
multiple fault conditions. There are different cross-domain feature distribution discrepancies between each health condition. Therefore, it is difficult to perform domain-invariant learning on both simulated and measured data under multi-class health conditions. The third challenge is that the health condition space of the target domain is usually unknown in real industrial scenarios. Unexpected fault mode shift causes negative transfer, which reduces model performance. These issues would impede the digital twin techniques for broad applications in industrial practices.

To address the aforementioned issues, a novel digital twin-driven rolling bearing fault diagnosis method is developed in this paper. The overview of the proposed method is given in Fig. 2. First, a dynamic model-based digital twin model that reflects the operating condition of the actual rolling bearing is established, which is used to obtain a sufficient simulated fault dataset. Through the digital twin model, various operating conditions and fault failure modes of the rolling bearing can be well simulated, thereby saving a lot of manpower and material costs from labeling data. Then, a Transformer-based cross-domain deep neural network is developed to learn and transfer diagnosis knowledge from the labeled simulated data to the unlabeled measured data. In this way, accurate fault diagnosis of rolling bearings can be achieved with limited unsupervised measured data. The main contributions of this work are summarized as follows:

- A general high-fidelity digital twin model for the rolling bearing is established, in which a dynamic model is developed to simulate the operating condition of rolling bearings. This model only requires the structural parameters of the bearing and the fault size to obtain the vibration response of the system.
- A transfer learning algorithm based on selective adversarial strategy is developed to implement partial domain adaptation learning. This method can reduce feature distribution discrepancy between simulated data and measured data, and it can also select out the outlier source health condition and promote positive transfer.
- Extensive experiments on experimental test-rig are conducted to show that the proposed method can provide an efficient and useful solution to the fault diagnosis of practical industrial bearings.

The organization of this paper is as follows: Section 2 describes the real rolling bearing physical test rig and the corresponding digital twin model. The proposed Transformer-based deep transfer learning model is developed
in Section 3. The experimental verification is discussed in Section 4. The conclusions are drawn in Section 5.

2. Digital twin model of rolling bearing

The digital twin technique mainly includes three parts: a physical entity in real space, a digital model in virtual space, and the information connection between the physical entity and the digital model. This section will introduce the actual rolling bearing physical test rig (physical asset) and the proposed rolling bearing digital twin model.

2.1. Physical entity of rolling bearing test rig

To investigate the bearing diagnosis performance based on digital twin, a rolling bearing fault simulation test rig is applied as shown in Fig. 3. The test rig is supported by two rolling bearings, and the right bearing is used as the test bearing. Two accelerometers are arranged in the horizontal and vertical directions of the bearing house to collect the vibration signal with a sampling frequency of 20 kHz. The vibration signal of the vertical direction is used in this study. During the experiment, three bearing fault conditions, namely, outer race fault (OF), inner race fault (IF), and ball fault (BF) are manually customized, along with a normal (N) condition for a total of four health conditions. The three types of fault bearing are shown in Fig. 4, and the width and depth of the faults are 1 mm and 0.5 mm, respectively. The OF and BF use N205EM cylindrical roller bearings, and the IF uses NU205EM cylindrical roller bearings. The structural parameters of these two types of bearings are shown in Table 1. In this test rig, the data of three types of fault conditions and one type of health condition are collected at the motor speeds of 1200 rpm and 1800 rpm, respectively.
2.2. Digital twin model of rolling bearing

In this paper, a digital twin model is established to characterize the dynamic response of the bearing system. Fig. 5 is the five-degree-of-freedom dynamic model of rolling bearing. The inner ring and outer ring have two degrees of freedom respectively, namely horizontal translational displacement $x_i$, $x_o$, and vertical translational displacement $y_i$, $y_o$. The unit resonator has one degree of freedom only, namely the vertical translational displacement $y_r$.

The rotational speed of the cage can be written as:

$$
\omega_c = \frac{\omega_s}{2} \left( 1 - \frac{d \cos \alpha}{D} \right)
$$

(1)

where $\omega_s$ is the shaft rotating speed, $d$ represents the diameter of the roller, $D$ stands for the pitch diameter, and $\alpha$ is the contact angle.

The angular position of the $j$-th roller is given by:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>N205EM</th>
<th>NU205EM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diameter of outer ring ($D_o$/mm)</td>
<td>52</td>
<td>52</td>
</tr>
<tr>
<td>Diameter of inner ring ($D_i$/mm)</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>Pitch diameter ($D$/mm)</td>
<td>38.5</td>
<td>38.5</td>
</tr>
<tr>
<td>Roller diameter ($d$/mm)</td>
<td>6.5</td>
<td>7.5</td>
</tr>
<tr>
<td>Number of rollers $n_b$</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>Contact angle ($\alpha/\circ$)</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1: Parameters of cylindrical roller bearings of N205EM and NU205EM.
where $n_b$ indicates the number of rollers.

The contact deformation between the $j$-th roller and raceways can be written as:

$$
\delta_j = (x_i - x_o) \cos \theta_j + (y_i - y_o) \sin \theta_j - \gamma
$$

where $\gamma$ denotes the radial clearance.

The Hertzian contact force in horizontal and vertical directions can be written as:

$$
F_x = \sum_{j=1}^{n_b} K\delta_j^{10/9} \cos \theta_j
$$

$$
F_y = \sum_{j=1}^{n_b} K\delta_j^{10/9} \sin \theta_j
$$

where $K$ is the contact stiffness.

The kinetic differential equations are expressed as:

$$
\begin{cases}
    m_i \ddot{x}_i + c_i \dot{x}_i + k_i x_i + F_x = 0 \\
    m_i \ddot{y}_i + c_i \dot{y}_i + k_i y_i + F_y = W + m_i g \\
    m_o \ddot{x}_o + c_o \dot{x}_o + k_o x_o - F_x = 0 \\
    m_o \ddot{y}_o + (c_o + c_r) \dot{y}_o + (k_o + k_r) y_o - k_r y_r - c_r \dot{y}_r - F_y = m_o g \\
    m_r \ddot{y}_r + c_r \dot{y}_r + k_r (y_r - y_o) + k_r (y_r - y_o) = 0
\end{cases}
$$

where $m_i$, $m_o$, $m_r$ are the mass of inner race, outer race and unit resonator respectively, $c_i$, $c_o$, $c_r$ are the damping of inner race, outer race and unit resonator respectively, $k_i$, $k_o$, $k_r$ are the stiffness of inner race, outer race and unit resonator respectively, $W$ is the radial load applied to the inner race.

In this dynamic model, three fault conditions are simulated, namely outer ring fault, inner ring fault, and roller fault. Localized defects are modeled as rectangular spalls as shown in Fig. 6.

As shown in Fig. 6(a), the circumferential span angle of the outer defect can be written as: $	heta_j = \omega_c t + \frac{2\pi(j - 1)}{n_b}$
\[ \beta_o = \arcsin \frac{L_o}{D_o} \]  

(7)

where \( L_o \) is the width of the outer defect, \( D_o \) denotes the diameter of the outer race.

When the \( j \)-th roller approaches the spall, the expression of the position relationship is as follows:

\[ | \mod (\theta_j, 2\pi) - \theta_D| < \beta_o \]  

(8)

where \( \theta_D \) is the angular position of the defect.

When the roller passes the defect, it will release a small amount of deformation. The loss of contact deformation can be calculated as:

\[ \delta_o = \frac{d}{2} - \sqrt{\left(\frac{d}{2}\right)^2 - \left(\frac{L_o}{2}\right)^2} \]  

(9)

Then the contact deformation between the roller and raceways when the roller passes the defect is given by:

\[ \delta_j = (x_i - x_o) \cos \theta_j + (y_i - y_o) \sin \theta_j - \gamma - \delta_o \]  

(10)

As shown in Fig. 6(b), the circumferential span angle of the inner defect can be written as:

\[ \beta = \arcsin \frac{L_i}{D_i} \]  

(11)

where \( L_i \) is the width of the inner defect, \( D_i \) represents the diameter of the inner race.

When the spall is located in the inner race, the spall will rotate with the inner ring. The expression of the position relationship when the defect contacts the roller is as follows:

\[ | \mod (\theta_i, 2\pi) - \mod (\theta_j, 2\pi)| < \beta_i \]  

(12)

where \( \theta_i \) is the angular position of the inner race defect, \( \theta_i = \omega_i \times t. \)

When the inner defect contacts the roller, the loss of contact deformation can be calculated as:
\[
\delta_i = \frac{d}{2} - \sqrt{\left(\frac{d}{2}\right)^2 - \left(\frac{L_i}{2}\right)^2}
\]  

(13)

And the contact deformation between the roller and raceways when the roller passes the inner defect is given by:

\[
\delta_i = (x_i - x_o) \cos \theta_j + (y_i - y_o) \sin \theta_j - \gamma - \delta_i
\]  

(14)

As shown in Fig. 6(c), the circumferential span angle of the roller defect can be written as:

\[
\beta_r = \arcsin \frac{L_r}{d}
\]  

(15)

where \(L_r\) is the width of the roller defect.

When the spall is located on the roller, the spall will rotate with the roller. The expression of the position relationship when the roller defect contacts the raceways is expressed as:

\[
\left| \text{mod} \left( \varphi_j, 2\pi \right) - \frac{\pi}{2} \right| < \beta_r
\]  

(16)

\[
\left| \text{mod} \left( \varphi_j, 2\pi \right) - \frac{3\pi}{2} \right| < \beta_r
\]  

(17)

where \(\varphi_j\) is the angular position of the roller defect, which can be calculated by:

\[
\varphi_j = \frac{\omega_s D}{2} \left( 1 - \left( \frac{d}{D} \cos \alpha \right)^2 \right) t
\]  

(18)

When the roller defect contacts the raceways, the loss of contact deformation can be calculated as:

\[
\delta_r = \frac{d}{2} - \sqrt{\left(\frac{d}{2}\right)^2 - \left(\frac{L_r}{2}\right)^2}
\]  

(19)

Then, the contact deformation between the roller and raceways when the roller defect contacts the raceways is given by:

\[
\delta_j = (x_i - x_o) \cos \theta_j + (y_i - y_o) \sin \theta_j - \gamma - \delta_r
\]  

(20)

The vibration response of the bearing will be obtained by solving Eq. 6 using the fourth-order fixed-step Runge-Kutta method. The calculation time step is \(5 \times 10^{-5}\) s.

2.3. Digital twin model validation

To verify the rationality of the digital twin model, the measured acceleration signals and the corresponding simulated acceleration signals are visualized for comparison. The bearing types and their parameters as given in Table 1 are adopted in the simulation model. Based on the structural parameters of the bearing, the fault characteristic frequency of the inner ring, outer ring, and roller are shown in Table 2. Under the parameters of the experimental bearing, the virtual data of the bearing under normal and fault conditions can be obtained from the dynamic model. In this paper, the bearing acceleration responses in the vertical direction are used for fault
diagnosis tasks. Take the rotating speed of 1200 rpm as an example, the time-domain waveform and envelope spectrum comparisons of the simulated signal and the measured signal under the faults of the outer ring, ball, and inner ring are shown in Fig. 7, Fig. 8, and Fig. 9 respectively. When the rotating speed is 1200 rpm (the rotating frequency \( f_r = 20 \text{ Hz} \)), the theoretical fault frequency of the OF, BF, and IF are 108.1Hz, 115.1Hz, and 155.3Hz, respectively. It can be observed that rolling bearing faults generate periodic impulses in the time-domain signals of simulation and measurement, and the impulse trends of the simulated signals and measured signals for each fault are similar. For the envelope spectrum, it can be found that the prominent bearing frequency components of the simulated signal are consistent with the theoretical values, and the measured signal and simulated signal have the same frequency components. This fully proves the effectiveness of the digital twin model established in this paper. Thus, the vibration response under various bearing fault modes can be obtained from the established model.

### Table 2: Equations of bearing fault frequencies.

<table>
<thead>
<tr>
<th>Fault conditions</th>
<th>Fault passing frequencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ball-pass frequency at outer ring</td>
<td>( f_o = \frac{n_b}{2} \left( 1 - \frac{d}{D} \cos \alpha \right) f_r = 5.4026 f_r )</td>
</tr>
<tr>
<td>Ball-pass frequency at inner ring</td>
<td>( f_i = \frac{n_b}{2} \left( 1 + \frac{d}{D} \cos \alpha \right) f_r = 7.7662 f_r )</td>
</tr>
<tr>
<td>Ball-spin frequency</td>
<td>( f_b = \frac{D}{d} \left[ 1 - \left( \frac{d}{D} \cos \alpha \right)^2 \right] f_r = 5.7542 f_r )</td>
</tr>
</tbody>
</table>

Figure 7: Waveform and envelope spectrum of the simulated signal and the measured signal under outer race fault.

3. Proposed digital twin-drive domain adaptation model

3.1. Problem definition

Once the dynamic model of the rolling bearing is established, we can simulate the vibration response of the bearing system under various fault conditions. For a rolling bearing in an actual industrial scenario, it is difficult to obtain the vibration signals in all fault conditions in advance. Thus, the partial domain adaptation problem is investigated in this study. Let \( D^s = \{ x^s_i, y^s_i \}_{i=1}^{n_s} \) denote the source domain simulated data, where \( n_s \) is the number of samples, \( x^s \) and \( y^s \) are the source domain samples and labels, respectively. Let \( D^t = \{ x^t_i \}_{i=1}^{n_t} \) represent the target domain measured data, where \( n_t \) is the number of samples, \( x^t \) are target domain samples. The label sets of
the source domain and target domain are defined as \( C_s \) and \( C_t \), respectively. This work mainly focuses on partial domain adaptation scenario, i.e., \(|C_s| > |C_t|\). \( C = C_s \cap C_t \) denotes the shared label space, namely the classes existing in both domains. \( C_s = C_s \setminus C_t \neq \emptyset \), where \( C_s \) represents source-private classes also known as outlier classes. Outlier samples can easily lead to a negative transfer of a transfer model, thereby affecting the diagnostic performance of the model. This paper aims to design a deep transfer learning model to extract and transfer the diagnosis knowledge from the simulated data to measured data when the health condition space of the measured data is unknown.

3.2. Model description

The overall network architecture of the proposed digital twin-drive domain adaptation method is shown in Fig. 10 which consists of a feature extractor F, a classifier C, and a domain discriminator D. First, the simulated source samples and measured target samples are simultaneously fed into the F to extract discrepant features of different health conditions. Then, an adversarial learning-based D is introduced into the shared feature space of
the simulated data and measured data to achieve domain-invariant. Finally, a linear classifier C is used to output predictions for both domains. In this study, $\theta_F$, $\theta_C$, and $\theta_D$ represent the parameters of the F, C, and D, respectively. The three modules are described in detail below.

3.2.1. Feature extraction module

A Transformer-based network is built in the feature extractor. The proposed Transformer follows the original ViT Transformer block [47], whose structure framework is shown in Fig. [11] The Transformer block consists of multiheaded self-attention (MSA) and multilayer perception (MLP) blocks. Layer normalization is applied before each block and residual connections after each block. The MLP block contains two fully connected layers and a GELU nonlinearity. The main module of the Transformer block is MSA, and its function is to capture long-range dependencies between sequences. The multi-head self-attention mechanism is composed of multiple heads applying the self-attention function. Generally, a group of input embeddings $x$ is first transformed to $d_{\text{model}}$-dimensional keys, values, and queries, respectively:

$$Q_j = xW^q_j, \quad K_j = xW^k_j, \quad V_j = xW^v_j$$

where $W^q_j, W^k_j \in \mathbb{R}^{d_{\text{model}} \times d_k}$ and $W^v_j \in \mathbb{R}^{d_{\text{model}} \times d_v}$ are trainable projection matrices. By scaling the factor $\frac{1}{\sqrt{d_k}}$, a single-head scaled dot-product attention is computed as:

$$\text{Attention}(Q, K, V)_j = \text{Softmax}\left(\frac{Q_jK^T_j}{\sqrt{d_k}}\right)V_j$$

To jointly attend to information from different representation subspaces at different positions, multi-head attention is introduced. Similarly, it executes the single-head attention $H$ times. Thus, multi-head attention can be defined as:

$$\text{MSA}(Q, K, V) = \text{Concat}\left(\text{head}_j\right)_{j=1}^{H} W^O$$

$$\text{head}_j = \text{Attention}(Q, K, V)_j, j = 1, 2, \ldots, H$$
where \( W^O \in \mathbb{R}^{Hd_v \times d_{model}} \) is the trainable projection matrix, \( H \) represents the number of the attention heads.

In addition to multi-head self-attention, each Transformer block consists of an MLP feed-forward network. The MLP consists of two fully connected layers with a GELU activation in between, which can be defined as:

\[
MLP(x) = \text{GELU}(0, xW_1 + b_1)W_2 + b_2
\]

The input of the Transformer block is a one-dimensional sequence of token embeddings. We first establish an embedding processing method for one-dimensional vibration signals. This process is shown in Fig. 11. First, the input sample \( x \) of length \( L \) from each sensor is split into \( C \) segments of length \( S \) to form the patch sequences.

\[
x = [x_1^1; x_2^1; \cdots; x_C^1] \in \mathbb{R}^{C \times S}
\]

where \( C \) is the number of patches.

Then, these patches are mapped to the latent vector by a linear transformation layer, which generates patch embeddings. The dimension of the generated patch embedding remains the same as that of the original patch in this study. In addition, a randomly trainable embedding class token is introduced to the patch embeddings. To retain positional information in Transformer blocks, it is necessary to add position information to the patch embeddings. Thus, the final input of the Transformer block is described as follows:

\[
x' = [x_{CLS}; Lx_1^1; Lx_2^1; \cdots; Lx_C^1] + E_{pos}
\]

where \( L \) is the linear transformation, \( x_{CLS} \in \mathbb{R}^S \) denotes the class token, \( x_p^l \in \mathbb{R}^S \) is the patch tokens, \( E_{pos} \in \mathbb{R}^{(C+1) \times S} \) denotes the position embedding.

Finally, \( L \) Transformers of the same structure are used to extract high-level feature vectors, which can be expressed as:

\[
\begin{align*}
z'_l &= \text{MSA} \left( \text{LayerNorm} \left( z_{l-1} \right) \right) + z_{l-1} \\
z_l &= \text{MLP} \left( \text{LayerNorm} \left( z'_l \right) \right) + z'_l \\
h &= z_L^0
\end{align*}
\]
where $l = 1, 2, \ldots, L$ represents the $l$-th Transformer block, $h$ denotes the class token output from the last Transformer block.

The class token of the source and target domains is generated from the last Transformer block, which is then utilized as the input of the classifier and domain discriminator to reduce the feature distribution discrepancy of the two domains and obtain fault diagnosis results.

### 3.2.2. Domain discriminator module

In this study, our goal is to deal with cross-domain fault diagnosis between the simulated data and measured data. Domain-invariant learning is an essential strategy for this case. To this end, a domain adversarial neural network is developed to reduce feature distribution discrepancy between the simulation domain and the real-world domain. In the domain adversarial neural networks, the adversarial learning strategy [48] is usually adopted to implement domain-invariant learning, which the optimization objective can be described as:

$$
L_{dis} (x^s, x^t) = -\frac{1}{n_s + n_t} \sum_{x_i \in \mathcal{D}_s \cup \mathcal{D}_t} L_{ce} (D (F (x^s_{i})), d_i)
$$

(29)

where the $d_i$ denotes the domain label, $F$ defines the shared feature space of the two domains, and $L_{ce}$ is cross-entropy loss, which can be calculated by:

$$
L_{ce} (x, y) = -\mathbb{E}_{(x, y) \in \mathcal{D}} \left[ \sum_{k=1}^{K} I_{[k=y]} \log (\hat{y}_k) \right]
$$

(30)

where $y$ is the label of input sample $x$, $\hat{y}_k$ defines the predicted label, and $K$ is the number of health conditions. To achieve domain-invariant learning by using cross-entropy loss, the gradient reversal layer (GRL) is introduced in the shared feature layer for adversarial learning [48].

For the digital twin-driven cross-domain fault diagnosis tasks, monitoring data of various health conditions can be obtained through simulation models. Therefore, a complete dataset of common faults of rolling bearings can be established through the simulation model. However, the type of fault that occurs is often unknown for the monitoring data collected in real-world industrial scenarios. That is, the fault category of the measured data is usually a part of the fault category in the simulation data. In this case, implementing the global domain adaptation of the source domain distribution and the target domain distribution will cause a negative transfer of the model due to the samples of source outlier conditions. Moreover, the more outlier fault conditions in the simulation data space, the more severe the negative transfer effect. To solve this problem, we need to filter out samples of outlier conditions and the related conditions from the source domain during the domain adaptation process.

To match the simulated and measured data of nonidentical health condition spaces $C_s \neq C_t$, the selective adversarial network is introduced to implement partial domain adaptation [49]. We need to split the $\mathcal{D}$ into $|C_s|$ class-wise domain discriminators $D^k$, where $k$ represents the source domain health conditions, i.e., $k = 1, \ldots, |C_s|$. Each $D^k$ performs domain adaptation of source domain samples and target domain samples with health condition $k$. Since the health condition space $|C_t|$ of the target domain is unknown, it is not easy to determine which health condition $D^k$ needs to be executed. Fortunately, for a input sample $x_i$, its predicted output $\hat{y}_k = C (F (x_i))$ is a probability distribution over the $C_s$, which nicely describes the probability of assigning $x_i$ to each health condition. Thus, we can use the probability output to arrange each input sample $x_i$ to the corresponding $D^k$. This process can be expressed as:
\[ L_{\text{dis}}' (x^s, x^t) = -\frac{1}{n_s + n_t} \sum_{k=1}^{[C_s]} \sum_{x_i \in D_s \cup D_t} \hat{y}_i^k \mathcal{L}_{ce}^{k} (D^k (F (x_i)), d_i) \]  

(31)

where \( D^k \) denotes the \( k \)-th domain discriminator.

Compared with the traditional adversarial loss in Eq. 29, the established multi-discriminator network can effectively avoid the negative transfer of outlier samples and promote the positive transfer of each instance through the probability weighting mechanism of the instance level.

In the selective adversarial, a class-level weighting strategy is also introduced to further reduce the impact of outlier samples and improve the connection of shared health conditions. Theoretically, the domain discriminators responsible for the target health conditions \( C_t \) can promote the positive transfer of the model, while the domain discriminators responsible for the outlier health conditions \( C_s = C_s \setminus C_t \) in the source domain usually introduce noise and weaken the positive transfer of the model. Thus, we can reduce the introduction of noise and improve the positive transfer effect by reducing the weight of the domain discriminators of the outlier health conditions of the source domain, and this loss can be expressed as:

\[
L_D (x^s, x^t) = -\frac{1}{n_s + n_t} \sum_{k=1}^{[C_s]} \left( \frac{1}{n_t} \sum_{x_i \in D_t} \hat{y}_i^k \right) \times \left( \sum_{x_i \in (D_s \cup D_t)} \hat{y}_i^k \mathcal{L}_{ce}^{k} (D^k (F (x_i)), d_i) \right) 
\]

(32)

where \( \frac{1}{n_t} \sum_{x_i \in D_t} \hat{y}_i^k \) represents the class-level weight for health condition \( k \).

Although the \( L_D \) can selectively transfer relevant diagnostic knowledge by reducing the negative impact of outlier health conditions, it is highly dependent on the probability of \( \hat{y}_i = C (F (x_i)) \). Therefore, the entropy minimization strategy [50] is introduced to further enhance the separability among different health conditions and improve the prediction accuracy of target samples. This process is achieved by minimizing the prediction entropy \( L_E \) over probability \( \hat{y}_i^k \) on the target domain. The loss \( L_E \) can be obtained by:

\[
L_E (x^t) = \frac{1}{n_t} \sum_{x_i \in D_t} H (C (F (x_i)))
\]

(33)

where \( H (\cdot) \) denotes the conditional-entropy loss.

### 3.2.3. Classifier module

There are two fully connected layers in the classifier, in which the cross-entropy loss is utilized to learn discriminative features, which can be defined as:

\[
L_C (x^s, y^s) = -\frac{1}{n_s} \sum_{x_i \in D_s} \mathcal{L}_{ce} (\hat{y}_i^s, y_i^s)
\]

(34)

### 3.3. Total optimization objective

The total loss of the proposed partial domain adaptation network includes three terms given in Eq. 32, Eq. 33, and Eq. 34 which can be expressed as:

\[
L_{\text{total}} = L_C (x^s, y^s) + \lambda L_D (x^s, x^t) + \beta L_E (x^t)
\]

(35)
where $\lambda$ and $\beta$ represent tradeoff parameters. Based on this loss term, the network parameters $\theta_F$, $\theta_C$, and $\theta_D$ will be updated as follows:

$$
\begin{align*}
\theta_F &\leftarrow \theta_F - \eta \left( \frac{\partial L_C}{\partial \theta_F} + \lambda \frac{\partial L_D}{\partial \theta_F} + \beta \frac{\partial L_E}{\partial \theta_F} \right) \\
\theta_C &\leftarrow \theta_C - \eta \left( \frac{\partial L_C}{\partial \theta_C} + \beta \frac{\partial L_E}{\partial \theta_C} \right) \\
\theta_D &\leftarrow \theta_D - \eta \left( \frac{\partial L_D}{\partial \theta_D} \right)
\end{align*}
$$

(36)

3.4. Implementation of the diagnostic solution

In this paper, a digital twin-driven bearing fault diagnosis framework is established. The detailed implementation process of the proposed method is as follows.

- Measured data and simulated data sampling. Collect the fault signals of the bearing. Establish the dynamic model of the bearing and obtain the simulated fault dataset.
- Data preprocessing. Set the simulation data and test data as the source domain and target domain respectively. Then divide the samples according to the input data requirements of the model.
- Model initialization. Implement random parameter initialization for the model.
- Model training. Feed the training data of the source and target domains into the proposed model for training. The network parameters of the source and target domains are shared. The total objective function given by Eq. (35) is employed.
- Model testing. Feed the measured data into the trained model to test the model’s performance.

Once this process is completed, the proposed digital twin-driven fault diagnosis method can perform bearing fault diagnosis in practical industrial scenarios.

4. Experiment and result analysis

4.1. Experimental design and setup

4.1.1. Cross-domain diagnosis task

In this paper, our goal is to conduct digital twin-driven cross-domain fault diagnosis of rolling bearings. The simulated data is used as the source domain data, and the measured data is used as the target domain data. In the measured dataset, bearing monitoring data of four health conditions are collected at two rotating speeds, namely 1200 rpm and 1800 rpm. At the same time, we obtain the simulated data of the four health conditions under the rotating speeds 1200 rpm and 1800 rpm through the digital twin model. The measured data and the corresponding simulated data are described in detail in Section 2. Based on the simulated and measured data under two operating conditions, two experimental cases are designed, namely Case A: Simulated data (1200 rpm) $\rightarrow$ Measured data (1200 rpm), and Case B: Simulated data (1800 rpm) $\rightarrow$ Measured data (1800 rpm), where “$\rightarrow$” defines “source domain $\rightarrow$ target domain”. In each case, some cross-domain fault diagnosis tasks are designed to evaluate the general performance of the proposed method under partial domain adaptation scenarios and closed-set domain
adaptation scenarios. The cross-domain fault diagnosis tasks in two cases are shown in Table 3 and Table 4, respectively.

### 4.1.2. Parameter settings

The data point of each sample is $1 \times 2048$. For the Transformer encoder, the number of Transformer blocks is 6, the number of attention heads is 8, and the hidden dimension is 256. For the classifier, the output channels for two fully connected layers are 50 and $k_s$, where $k_s$ is the number of health conditions of the source domain. The domain discriminators consist of two fully connected layers with output dimensions of 10 and 1. During training, the initial learning rate is reduced by half every 50 epochs. The other related parameters are given in Table 5, where $k_s$ and $k_t$ define the numbers of health conditions of the source and target domains, respectively. After the training, the diagnostic accuracy of the measured data is utilized to evaluate the diagnostic performance of the model. All experiments are performed 6 times to reduce the randomness of deep learning methods.

<table>
<thead>
<tr>
<th>Table 5: Main Parameter Selection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>Simulated/Measured training samples</td>
</tr>
<tr>
<td>Simulated/Measured test samples</td>
</tr>
<tr>
<td>Simulated/Measured validation samples</td>
</tr>
<tr>
<td>Batch size</td>
</tr>
<tr>
<td>Dropout</td>
</tr>
</tbody>
</table>

Table 3: The digital twin-drive fault diagnosis tasks for Case A

<table>
<thead>
<tr>
<th>Task</th>
<th>Source domain health conditions</th>
<th>Target domain health conditions</th>
<th>Domain adaptation problem</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$</td>
<td>OF, IF, BF, N</td>
<td>IF, BF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$A_2$</td>
<td>OF, IF, BF, N</td>
<td>OF, BF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$A_3$</td>
<td>OF, IF, BF, N</td>
<td>OF, IF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$A_4$</td>
<td>OF, IF, BF, N</td>
<td>OF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$A_5$</td>
<td>OF, IF, BF, N</td>
<td>IF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$A_6$</td>
<td>OF, IF, BF, N</td>
<td>BF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$A_7$</td>
<td>OF, IF, BF, N</td>
<td>OF, IF, BF, N</td>
<td>Closed set</td>
</tr>
</tbody>
</table>

Table 4: The digital twin-drive fault diagnosis tasks for Case B

<table>
<thead>
<tr>
<th>Task</th>
<th>Source domain health conditions</th>
<th>Target domain health conditions</th>
<th>Domain adaptation problem</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_1$</td>
<td>OF, IF, BF, N</td>
<td>IF, BF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$B_2$</td>
<td>OF, IF, BF, N</td>
<td>OF, BF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$B_3$</td>
<td>OF, IF, BF, N</td>
<td>OF, IF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$B_4$</td>
<td>OF, IF, BF, N</td>
<td>OF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$B_5$</td>
<td>OF, IF, BF, N</td>
<td>IF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$B_6$</td>
<td>OF, IF, BF, N</td>
<td>BF, N</td>
<td>Partial</td>
</tr>
<tr>
<td>$B_7$</td>
<td>OF, IF, BF, N</td>
<td>OF, IF, BF, N</td>
<td>Closed set</td>
</tr>
</tbody>
</table>
4.1.3. Comparative methods

Five popular methods based on deep neural networks are conducted for comparative study to verify the advantage of the proposed method. To fairly highlight the advantages of the proposed method, the parameter optimization process of all comparative methods is performed to obtain high-performance model parameters.

- **Non-DA.** A non-domain adaptation method (Non-DA) is first introduced to illustrate the effectiveness of the domain adaptation process. The network structure of this method is consistent with that of the proposed model. During model training, the established domain adaptation loss is removed.

- **DACD.** We also compare the proposed method with some state-of-the-art domain adaptation methods. First, a classifier discrepancy (DACD) \[51\] method is introduced for comparison. In this method, two same classifiers are used, and the classifier discrepancy loss of two classifiers is trained to achieve cross-domain fault diagnosis.

- **MMD.** Second, a general MMD-based domain adaptation method \[28\] is established for comparison, in which the MMD loss is introduced at the shared feature layer of the source and target domains.

- **DANN.** To verify the effectiveness of the established partial domain adaptation strategy, the DANN \[48\] is also introduced for comparison. In this model, a general domain discriminator is introduced at the shared feature layer of source and target domains. The network structure of this domain discriminator is consistent with that of the established domain discriminator in the proposed method.

- **CNN.** To verify the effectiveness of the established Transformer, a generic CNN is adopted as the feature extractor. In this model, we replace the proposed Transformer structure with four convolution modules. The proposed adversarial loss is introduced at the last shared feature layer.

4.2. Experimental results and analysis

4.2.1. Experimental results

The digital twin-driven cross-domain fault diagnosis results for Case A are reported in Table 6 and Fig 12. For Non-DA, the diagnostic performance in all tasks is poor, and there is a significant discrepancy in feature distribution between the simulated domain and the measured domain. Among the traditional deep domain adaptation methods DACD, MMD, and DANN, the DANN method achieves the highest diagnostic accuracy in the partial domain adaptation tasks \(A_1\)–\(A_6\), and its accuracy values are 74.20\%, 73.09\%, 72.57\%, 71.28\%, 72.32\%, and 69.54\%, respectively. While for these tasks, the average diagnostic accuracy obtained by the proposed method is 81.78\%, 79.24\%, 79.05\%, 80.14\%, 83.45\%, and 79.36\%, respectively. Accordingly, this result illustrates that the proposed method achieves significantly better diagnostic performance than traditional domain adaptation methods under partial domain adaptation scenarios. At the same time, we can also observe that with the increase of outlier categories in the source domain, the diagnostic performance of the proposed method has a greater advantage than the traditional domain adaptation methods. The reason for this is that with the increase of outlier health conditions of the source domain, the phenomenon of the negative transfer becomes more serious, thus significantly reducing the cross-domain diagnostic performance of traditional domain adaptation methods. This fully verifies the effectiveness of the partial domain adaptation method established in this paper. To verify the effectiveness of
the Transformer, a general CNN method is used for comparison. The diagnostic accuracy of the CNN method is 78.34%, 77.13%, 77.46%, 76.44%, 80.87%, and 75.78%, respectively. The diagnostic accuracy of the CNN method in all tasks is lower than the proposed method. This illustrates that the diagnostic performance of the Transformer established in this paper is significantly better than that of general CNN. In addition, it can be clearly seen that in all tasks for the closed-set domain adaptation task $A_7$, the diagnosis performance of this method is also slightly higher than the traditional method MMD and DANN, indicating that the proposed method is also suitable for the closed-set domain adaptation scenario.

In addition, the results of different tasks for Case B are reported in Table 7 and Fig 13. It can also be clearly seen that the diagnostic results obtained in Case B are consistent with Case A, which further verifies the robustness of the proposed method in this paper. Therefore, two experimental cases fully prove that the proposed method can achieve digital twin-driven fault diagnosis in unsupervised scenarios. Thus, the proposed method can release the requirements of existing deep learning models on labeled data, and facilitate the health management of crucial bearings.

Table 6: The statistic of the diagnosis accuracy and standard deviation for Case A (%)

<table>
<thead>
<tr>
<th>Method</th>
<th>Non-DA</th>
<th>DACD</th>
<th>MMD</th>
<th>DANN</th>
<th>CNN</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$</td>
<td>50.12±3.58</td>
<td>64.67±2.53</td>
<td>73.26±1.90</td>
<td>74.20±2.25</td>
<td>78.34±1.89</td>
<td>81.78±1.47</td>
</tr>
<tr>
<td>$A_2$</td>
<td>48.67±3.82</td>
<td>63.15±2.77</td>
<td>70.45±2.34</td>
<td>73.09±2.46</td>
<td>77.13±2.04</td>
<td>79.24±1.52</td>
</tr>
<tr>
<td>$A_3$</td>
<td>46.33±4.15</td>
<td>63.58±3.05</td>
<td>71.24±2.44</td>
<td>72.57±2.01</td>
<td>77.46±1.78</td>
<td>79.05±1.62</td>
</tr>
<tr>
<td>$A_4$</td>
<td>53.18±3.25</td>
<td>63.27±2.84</td>
<td>70.89±2.67</td>
<td>71.28±2.57</td>
<td>76.44±1.85</td>
<td>80.14±1.59</td>
</tr>
<tr>
<td>$A_5$</td>
<td>57.24±2.54</td>
<td>64.58±3.02</td>
<td>71.48±2.58</td>
<td>72.32±2.45</td>
<td>80.87±1.35</td>
<td>83.45±1.20</td>
</tr>
<tr>
<td>$A_6$</td>
<td>43.25±4.33</td>
<td>60.49±3.45</td>
<td>68.38±2.97</td>
<td>69.54±2.78</td>
<td>75.78±2.21</td>
<td>79.36±1.79</td>
</tr>
<tr>
<td>$A_7$</td>
<td>47.95±3.44</td>
<td>75.37±1.57</td>
<td>79.77±0.96</td>
<td>80.21±1.14</td>
<td>77.27±1.25</td>
<td>80.56±1.02</td>
</tr>
</tbody>
</table>

Figure 12: Diagnosis performance comparisons for Case A.

4.2.2. Visualization analysis

In this section, we consider the task $A_1$ as a case to perform feature visualization to better understand the advantages of the proposed method. Firstly, the t-SNE [52] technology is used to visualize the features learned by the feature extractor. The t-SNE results of the measured samples of all methods are shown in Fig. 14. As can be seen from Fig. 14, the features of the different health conditions obtained by Non-DA are mixed together, and there are a large number of misclassification samples when the source model is directly used for the target domain.
Table 7: The statistic of the diagnosis accuracy and standard deviation for Case B (%)

<table>
<thead>
<tr>
<th>Method</th>
<th>Non-DA</th>
<th>DACD</th>
<th>MMD</th>
<th>DANN</th>
<th>CNN</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>B_1</td>
<td>48.79±3.78</td>
<td>62.47±2.49</td>
<td>73.14±2.22</td>
<td>72.44±2.14</td>
<td>76.49±2.11</td>
<td>80.32±1.35</td>
</tr>
<tr>
<td>B_2</td>
<td>49.76±3.64</td>
<td>61.12±3.24</td>
<td>71.43±1.93</td>
<td>71.99±2.35</td>
<td>76.82±1.76</td>
<td>79.59±1.48</td>
</tr>
<tr>
<td>B_3</td>
<td>56.71±3.09</td>
<td>65.84±2.75</td>
<td>74.53±2.04</td>
<td>75.97±1.79</td>
<td>79.05±1.34</td>
<td>82.23±1.24</td>
</tr>
<tr>
<td>B_4</td>
<td>48.50±3.94</td>
<td>60.79±3.25</td>
<td>70.56±2.44</td>
<td>71.14±2.67</td>
<td>77.84±1.71</td>
<td>81.23±1.45</td>
</tr>
<tr>
<td>B_5</td>
<td>56.48±2.73</td>
<td>60.93±3.46</td>
<td>70.72±2.87</td>
<td>71.80±2.30</td>
<td>80.86±1.29</td>
<td>84.21±1.09</td>
</tr>
<tr>
<td>B_6</td>
<td>42.55±4.21</td>
<td>59.42±3.77</td>
<td>67.35±3.15</td>
<td>67.86±3.08</td>
<td>76.52±1.77</td>
<td>78.41±1.80</td>
</tr>
<tr>
<td>B_7</td>
<td>49.21±3.58</td>
<td>74.94±1.70</td>
<td>79.43±1.05</td>
<td>80.04±1.28</td>
<td>77.59±1.36</td>
<td>80.19±1.15</td>
</tr>
</tbody>
</table>

Figure 13: Diagnosis performance comparisons for Case B.

test. In addition, there are many features that overlap in the different health conditions for DACD, MMD, DANN, and CNN. In contrast, the feature distribution map acquired by the proposed method is more discriminative, and the decision boundary is relatively clear.

To more intuitively reflect the performance advantages of the proposed method, the confusion matrix visualization technique is used to display the diagnostic accuracy of all health conditions. We also consider the task A_1 as a case to perform the confusion matrix visualization, the results of all methods are shown in Fig 15. In this experiment, the source domain simulated data has four health conditions (IF, BF, N, and OF), and the target domain measured data has three health conditions (IF, BF, and N). The "nan" in the confusion matrices defines no OF in the ground-truth label. It is worth noting that a few samples are wrongly classified into the source private category in CNN and the proposed method. This shows that the partial domain adaptation process established in this paper can automatically identify private health conditions and the shared health conditions in the source domain, and independently conduct domain adaptation learning, thereby improving the cross-domain fault diagnosis performance of the model. In addition, compared with the popular CNN-based network structure, the Transformer-based model established in this paper offers better diagnostic performance in most health conditions. Therefore, the confusion matrix results further prove the effectiveness and superiority of the proposed method.

4.2.3. Hyperparameter selection analysis

In our experiments, the grid search technique is used for hyperparameter selection. The major hyper-parameters of the proposed method are dropout, initial learning rate, tradeoff parameter $\lambda$, and tradeoff parameter $\beta$. To reduce the number of hyper-parameters, $\lambda$ and $\beta$ are equal in our experiment. In the process of parameter selection, the parameter range is first set according to experience, and then the grid search is carried out for the preset parameter
range by the model training. Fig. 16 shows the accuracy curves of the proposed model during the hyperparameter selection processes. As can be shown, the hyperparameters used in this paper enable the model to operate with the best diagnostic accuracy. Furthermore, these hyperparameter changes within a reasonable range have no significant effect on model performance. This indicates that the model proposed in this paper has good stability.

5. Conclusion

The rolling bearing fault is a common phenomenon in the lifespan of rotating machinery, and the fault could result in unexpected economic loss and even severe incidents. Real-time fault diagnosis of the rolling bearing could provide significant benefits to industrial applications. In this paper, a digital twin-driven methodology was proposed for intelligent fault diagnosis of rolling bearings. A high-fidelity digital twin model was established to reveal the dynamic response of the rolling bearing under different health conditions. The partial domain adaptation algorithm was adopted to transfer the diagnosis knowledge learned from the digital twin model to the measured data of the physical test rig. The developed methodology could accurately diagnose the health conditions of practical rolling bearings with the measured data of unknown fault conditions and unknown labels. Moreover, a digital twin-driven cross-domain fault diagnosis experiment was carried out to verify the effectiveness of the developed methodology. The research results demonstrated that the proposed approach can provide an efficient solution for bearing fault diagnosis in some critical scenarios, thereby ensuring the safe and efficient operations of bearings. This would bring significant economic benefits to industry practices by reducing maintenance costs and unnecessary shutdowns. Moreover, the developed methodology could promote the wide application of digital twin techniques in bearing condition monitoring.

The bearing failure mechanisms are usually complex, and various failure modes can occur in actual industrial scenarios. Therefore, more failure models need to be considered and studied in our future research. In addition, identifying unknown fault modes in the target domain should be further explored in future research.
Figure 15: The confusion matrix of different methods at task A1.

Figure 16: Test accuracy curves of the hyperparameter selection processes.
6. Acknowledgement

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