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RESEARCH ARTICLE

DTM-Bearing: A Novel Framework for Speed-Invariant Bearing Fault Diagnosis Based on Diffusion Transformation Model (DTM)

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ABSTRACT Fault diagnosis holds important significance in mitigating financial losses and ensuring equipment safety. As a crucial aspect of industrial machinery, bearing fault diagnosis becomes imperative. Nevertheless, in reality, identifying faults becomes challenging due to the presence of diverse variations in abnormal data, such as different vibration rotational speeds. In this paper, a novel framework for bearing fault diagnosis is proposed, called *DTM-bearing*, built upon the diffusion transformation model (DTM). This approach can transfer signals across different vibration speeds into a standardized signal aligned with a speed template. The primary purpose of *DTM-bearing* is to eliminate speed variations and extract speed-invariant features. Consequently, bolster the robustness of bearing fault diagnosis across diverse vibration speed scenarios. To the best of our knowledge, the proposed method is the first to combine the concepts of diffusion model and transformation in the domain of bearing fault diagnosis. Various experiments are performed on some datasets with multiple different speeds, which shows proposal can effectively improve the performance of bearing diagnosis. The framework based on the diffusion transformation model is expected to eliminate additional variations and improve the effectiveness of bearing diagnosis in practical applications.

INDEX TERMS Bearing fault diagnosis, diffusion transformation model (DTM), *DTM-bearing* framework, speed-invariant.

I. INTRODUCTION

A. MOTIVATION

Fault diagnosis plays a significant role in mitigating financial losses and ensuring equipment safety. As an essential part of industrial machinery, bearings play a pivotal role in supporting rotating components and ensuring smooth operation. Any undetected faults in bearings can lead to severe consequences, including machinery breakdowns, costly repairs, and potential hazards to personnel and assets. The effective identification of bearing faults also plays a crucial role in preventing economic losses resulting from unexpected industrial shutdowns triggered by machinery failure [1]. Therefore, it is necessary to provide an accurate diagnosis of bearing faults.

However, bearing fault diagnosis is still challenging in real-world industrial settings. This is because there are many various influencing factors that would affect the vibration characteristics of bearings, such as high background noise, fluctuating working conditions, and different vibration rotational speeds of bearings. It is still necessary to keep developing and improving the existing bearing fault diagnosis.

In this paper, it mainly focuses on the influence factor of bearing rotational speed. This is because the rotational speed of bearing is various and there are many unknown

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rotational speeds of bearing in reality. This will cause it challenging to detect one signal under an unknown rotational speed. Along with the development of bearing fault diagnosis, it can roughly group two categories: based on traditional machine learning approaches [2], [3], [4], and based on deep learning approaches. In terms of traditional machine learning approaches, Sugumaran and Ramachandran [2] proposed SVM to classify different bearing fault types, and Cerrada et al. [4] used random forest (RF) to improve the accuracy. In addition to these traditional machine learning approaches, there are also some deep learning techniques. In 2017, Zheng et al. [5] proposed a method base on artificial neural network (ANN) and transfer learning for bearing vibration signals. However, this method is challenging to extract important features when transferred to the knowledge domain for further classification at different speeds. In order to increase the power of the network, Lu et al. [6] used the hierarchical convolution network to extract the invariant feature instead of a simple artificial neural network, and Shao et al. [7] employed a deep autoencoder network. Hasan and Kim [8] used the stockwell transform which is a time-window Fourier transform that has the advantages of both the short-term-Fourier transform and the wavelet transform. Yan et al. [9] employed a diffusion model to reconstruct the signal while not considering speed transfer learning. These approaches have defined multiple fault classification dimensions without relying on handcrafted features. However, these methods are not compatible very well under unknown dynamic rotational speeds in real scenarios.

Recently, some transformation models [10], [11] have been discovered to primarily excel when dealing with data that possesses relatively restricted variations, and verified that the generative transformation model can remove variations and effectively improve model robustness in the area of object recognition. These works use generative adversarial networks (GANs) to transfer any external variations into one template and remove the influence of these variations. The proposed method is inspired by these works [10], [11], and proposes a novel framework based on the diffusion transformation model in the area of bearing fault diagnosis.

B. METHOD OVERVIEW AND CONTRIBUTIONS

The overview of the proposed method can be shown in Figure 1. In the inference stage, input is a vibration signal with any rotational speed, it will be through the diffusion transformation model (DTM) to transfer the signal into a signal with a known speed template. And then, it will be through a simple MLP model to output the diagnosis result, normal baseline (NB), inner race fault (IRF), ball fault (BF), and outer race fault (ORF). The proposal has the following contributions:

- A novel framework for bearing fault diagnosis based on the diffusion transformation model (DTM) is introduced, called *DTM-bearing*, which can transfer one signal with any vibration speed into one signal under a speed template. The main purpose of *DTM-bearing* is to remove speed variation and extract speed-invariant features, and improve the robustness of bearing fault diagnosis under different vibration speeds condition. To the best of our knowledge, the proposed method the first to combine the concepts of diffusion and transformation on the bearing fault diagnosis task.
- Unlike traditional diffusion model algorithm [12] which is similar to a reconstruction model, a new diffusion transformation model (DTM) is presented which enables the diffusion model can transfer one source data into target data and achieve data transformation. In addition, instead of using the two stages to learn the bearing fault representative feature, the proposed method combines the DTM network and a simple MLP network to learn better representative features and can directly output the fault state.
- The Proposed method was evaluated on some bearing datasets with multiple different speeds and achieved a high recognition rate in comparison to other methods. The experiment results demonstrate that the *DTM-bearing* framework is an effective way to handle with various speed variants, and validate its potential for practical bearing fault diagnosis applications.

II. RELATED WORKS

This section will provide brief introductions about generative models' application in the area of rolling bearing fault diagnosis. Including Variational AutoEncoders (VAEs: focus on reducing dimension and data reconstruction), Generative Adversarial Networks (GANs: focus on data generating data for dataset balance), and Diffusion Model. Their basic network structure can be seen in Figure 2.

A. VARIATIONAL AUTOENCODERS (VAES)

Variational AutoEncoders (VAEs) [13] has emerged as a powerful tool in various fields, including rolling bearing fault diagnosis. VAEs is a powerful class of generative models that offer a sophisticated approach to learning compact representations of complex data. These models consist of two crucial components: an Encoder and a Decoder, as shown in Figure 2. The encoder's role is to transform input data into a lower-dimensional latent space, while the decoder reconstructs the original data from points in this latent space. What sets VAEs apart is their probabilistic approach, where the encoder defines a multivariate Gaussian distribution in the latent space, facilitating more effective sampling and interpolation of data points.

VAEs are generative models that can capture complex data distributions and perform data reconstruction while learning useful latent representations. In the context of bearing fault diagnosis, researchers have employed VAEs to reduce the noise and learn informative features from vibration signals. Martin et al. [14] used a fully unsupervised deep variational auto-encoder-based method to reduce the dimensional and extract feature capabilities for fault

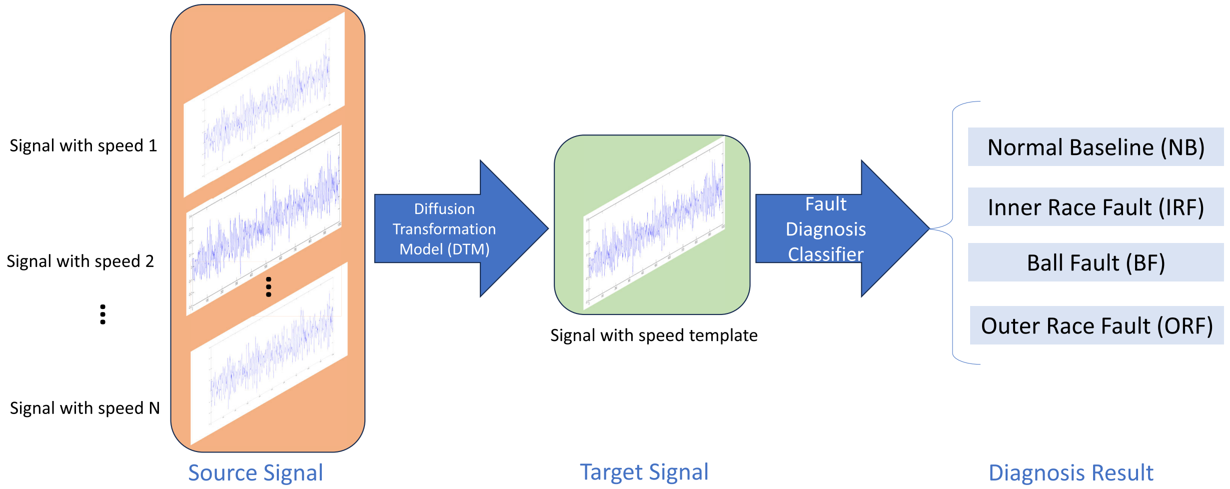

FIGURE 1. **The overview framework of *DTM-Bearing*: transfer one signal of varying vibration rotational speeds into a unified signal under a speed template. When facing an unknown speed signal, DTM will transfer it into a signal with a know speed template. (With input a signal, the DTM transfers it into signal with speed template, through a classifier, and finally outputs the result). The purpose of *DTM-Bearing* is to eliminate speed discrepancies and extract speed-invariant characteristics, leading to significantly enhancing the robustness of bearing fault diagnosis across diverse vibration speed conditions.**

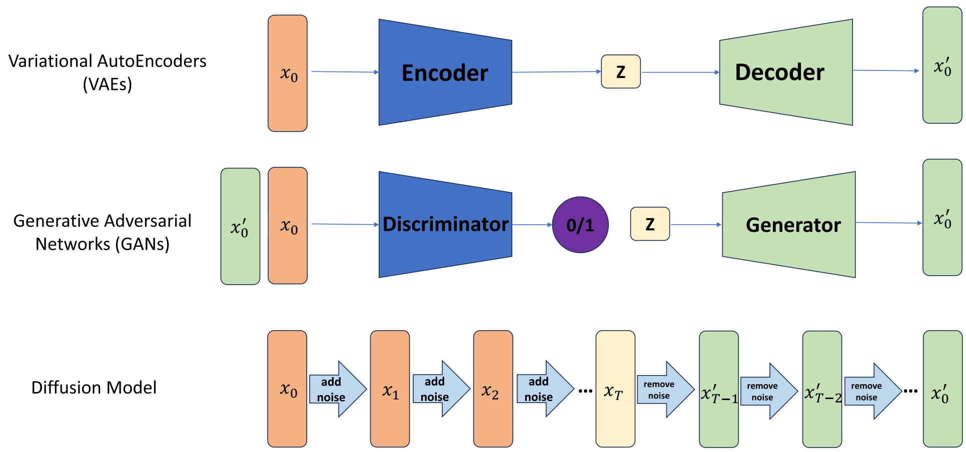

FIGURE 2. **The structures of three generative networks.**

diagnosis. Zhang et al. [15] used variational autoencoder (VAEs) generative models to propose a semi-supervised learning scheme for fault diagnosis, which can leverage a dataset when only a small subset of data have labels.

B. GENERATIVE ADVERSARIAL NETWORKS (GANS)

Generative Adversarial Networks (GANs) [16] have also made significant contributions to the field of rolling bearing fault diagnosis. At the core of a GAN, two primary components work in tandem: the Discriminator and the Generator, as shown in Figure 2. The Discriminator, often implemented as a convolutional neural network (CNN), serves as a classifier with the task of distinguishing between real data and fake data generated by the Generator. The Generator, on the other hand, is responsible for creating synthetic data samples. It begins with random noise as input and progressively refines these samples, often using transposed convolutional layers and non-linear activations, to produce data that aims to be indistinguishable from real examples.

The essence of GANs lies in a competitive training process: the Generator strives to produce data that fools the Discriminator, while the Discriminator seeks to improve its accuracy in telling real from fake. As training progresses, the Generator becomes increasingly adept at generating realistic data, leading to a delicate equilibrium in which it creates highly convincing samples. GANs have revolutionized image generation, style transfer, and more, making them a cornerstone of generative deep learning models. In this context, GANs have been used to generate realistic vibration signals to handle with limited imbalance data. Liu et al. [17] proposed a wavelet capsule generative adversarial network (WCGAN) to generate data for balancing datasets. Viola et al. [18] also proposed a methodology called FaultFace for failure detection on Ball-Bearing joints for unbalanced and contain little information.

C. DIFFUSION MODELS

Recently, diffusion model [19] has achieved state-of-the-art results in sample quality [20], denoising [12], and influence maximization [21], [22]. Examples like Stable Diffusion [23] model has achieved highly competitive performance on text-to-image synthesis, unconditional image generation and super-resolution. It consists of two key components: the Diffusion Process and the Denoising Process, as shown in Figure 2. The Diffusion Process is a method for gradually deteriorating an observed image. It starts with a clean image and iteratively adds noise, typically by applying a series of transformations. Each step increases the image's uncertainty and complexity, effectively diffusing it. The Denoising Process, conversely, aims to recover the original image from the noisy, diffused version. It employs a neural network, often called a denoiser, which takes the noisy image as input and uses its learned parameters to reduce the noise and uncertainty, progressively making the image clearer with each iteration.

Compared with VAEs and GANs, diffusion models directly estimate data likelihood, avoiding mode collapse, providing a clear generative process, and offering more stable training. This paper exploits the diffusion model in the area of rolling bearing fault diagnosis. Unlike the traditional VAEs approaches [14], [15] which focus on reducing dimension and data reconstruction, or traditional GANs approaches [17], [18] which focus on data generating data for dataset balance, the proposal would transfer one signal of varying vibration rotational speeds into a unified signal under a speed template by diffusion models.

III. METHODOLOGY

A. DIFFUSION TRANSFORMATION MODEL (DTM)

Diffusion Transformation Model (DTM) combines the concepts of diffusion and transformation, it consists of a diffusion process and a transformation process. DTM is the variant of Denoising Diffusion Probabilistic Models (DDPM) [12] which is similar to a reconstruction model. Different from DDPM [12], the DTM combines the concept of transformation which enable the diffusion model can transfer one source data into target data and achieve data transformation. The diffusion process will let the source signal add random noises several times, while the transformation process is to remove noise and transfer the latent signal into the target signal, as shown in Figure 3.

To effectively implement DTM in bearing fault diagnosis, the methodology setup begins with the selection of target (or template) signals for each health condition, such as normal and other fault conditions (Ball, Inner or Outer Race Fault), as shown in Figure 4. During the training phase, DTM learns to understand the relationships between different speeds and projects the original signals into a high-dimensional space. In this space, signals from normal conditions at varying speeds are aligned closer to the normal condition target signal. Similarly, signals from fault conditions are brought closer to the fault condition target signal.

The true strength of DTM is highlighted in the inference stage, where it demonstrates its capability not only to align known speed signals with the corresponding target signals but also to adapt unknown speed signals effectively to the nearest target signal. This ability greatly enhances the discriminative power of DTM, enabling it to identify different types of health conditions with higher precision. Consequently, DTM serves as a powerful tool in monitoring machine health conditions, providing a more robust and reliable means of diagnosing bearing faults in diverse operational speed environments.

1) DIFFUSION PROCESS

Give a signal x_0 with any vibration rotational speeds. The diffusion process will repeat adding Gaussian noise by T times. The forward trajectory, corresponding to starting at the signal x_0 distribution and performing T steps of diffusion, the equation as follows formula 1:

$$q(x_t|x_{t-1}) := \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t \boldsymbol{I}) \tag{1}$$

where t denotes step number, β_t denotes variance schedule. This processing is called *diffusion process* or *forward process*, is fixed to a Markov chain which gradually adds Gaussian noise to the data according to a variance schedule β_t.

For easy understanding, the initial signal x_0 will add one random Gaussian noise to become x_1, and add noise again become x_2, when repeat noise T steps, the x_0 would become x_T, is thus:

$$x_0 \rightarrow x_1 \rightarrow x_2 \cdots \rightarrow x_{T-1} \rightarrow x_T \tag{2}$$

2) TRANSFORMATION PROCESS

For the backward transformation process, it aims to transfer latent signal x_T into target signal x'_0 by denoising process, as shown in Figure 3, the equation as follows formula 3. The process is achieved by the neural network learning noise and removing noise step by step.

$$x_T \rightarrow x'_{T-1} \cdots \rightarrow x'_2 \rightarrow x'_1 \rightarrow x'_0 \tag{3}$$

Specifically, given the prior probability $q(x'_{t-1}|x'_t)$, the neural network will learn the posterior probability $p_\theta(x'_{t-1}|x'_t)$,

$$p_\theta(x'_{t-1}|x'_t) := \mathcal{N}(x'_{t-1}; \mu_\theta(x'_t, t), \Sigma_\theta(x'_t, t)) \tag{4}$$

where the μ_θ and Σ_θ represent signal mean and variance, respectively. Experimentally, set the $\Sigma_\theta(x'_t, t) = \sigma_t^2 \boldsymbol{I} = \beta_t$. The neural network will learn to predict the noise ϵ_θ, and get the x'_{t-1} from x'_t.

$$x'_{t-1} = \mu_\theta(x'_t, t) + \sigma_t z \tag{5}$$

$$\mu_\theta(x'_t, t) = \frac{1}{\sqrt{\alpha_t}}(x'_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(x'_t, t)) \tag{6}$$

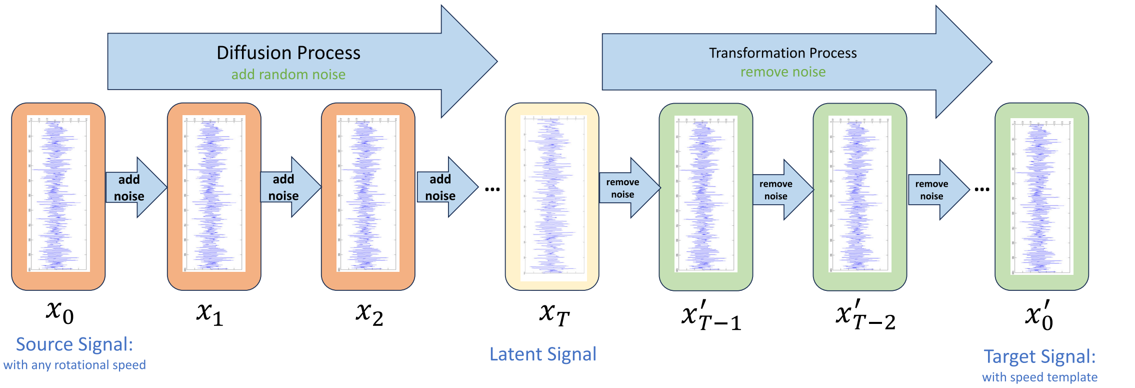

FIGURE 3. Diffusion Transformation Model (DTM). The diffusion process: add random noise. The transformation process: remove noise. Aim to transfer a signal with any vibration rotational speeds into a signal with a speed template, and remove speed variant for bearing fault diagnosis.

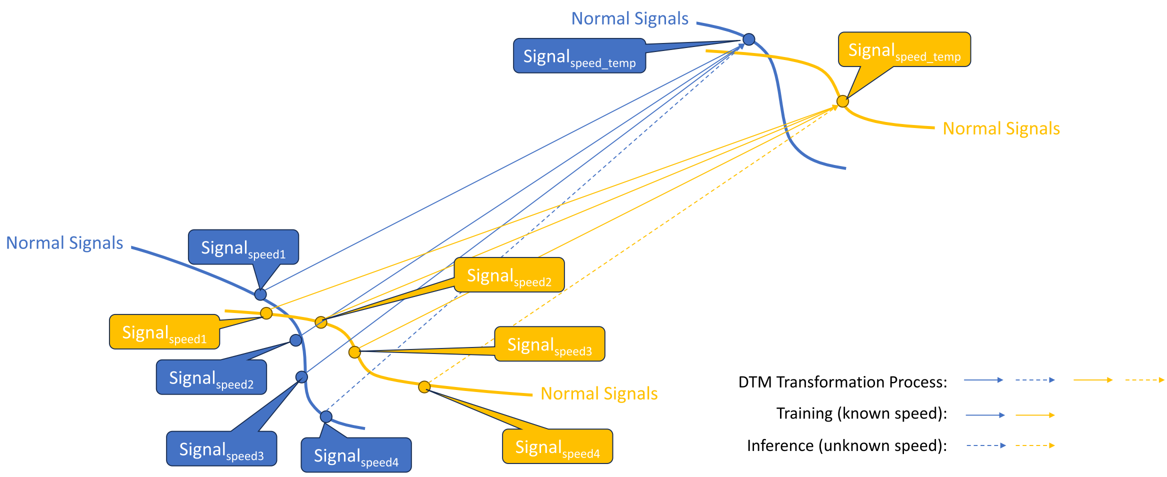

FIGURE 4. DTM presents a novel solution to these challenges. At the core of its functionality is the ability to standardize signals of varying speeds to a consistent 'template speed.' This transformation is pivotal in eliminating discrepancies caused by speed variations, thereby unveiling speed-invariant characteristics. The signal feature after DTM transformation is crucial in accurately detecting bearing faults, irrespective of the operational speed of the machinery.

where $z \sim \mathcal{N}((0, \boldsymbol{I}), \alpha_t = 1 - \beta_t$ and $\overline{\alpha}_t = \Pi_{s=1}^{t} \alpha_s$.

The Diffusion Transformation Model (DTM) emerges as a transformative approach, adept at handling the complexities posed by varying speed conditions. Traditional methods often grapple with two primary challenges when analyzing signals for bearing health assessment. Firstly, for signals under the same health condition, there is a noticeable spread in the distances between different speeds, complicating the analysis. Secondly, distinguishing between different health conditions becomes problematic as the distances between them tend to be smaller and more clustered, leading to potential misinterpretations. These two challenges can be effectively solved by the proposed Diffusion Transformation Model, as shown in Figure 4.

B. FAULT DIAGNOSIS CLASSIFIER

In terms of the fault diagnosis classifier, a simple 1D CNN is used to learn the fault representative feature and output the type of fault. The network is simple and only includes two 1D convolutional layers and two PReLU activate function layers. This is because the signal becomes easier to distinguish fault conditions after through diffusion transformation model (DTM). The DTM will transfer vibration rotational speeds into one template speed, so the transferred signal has the speed-invariant feature.

In the experiment, the softmax loss can classify the input into different classes. softmax loss is used many areas [24] and achieve a good result. Softmax loss can enlarge the inter-class variation and minimize the intra-class variation.

$$L_{softmax} = -\sum_{i=1}^{m} \log \frac{e^{W_{y_i}^T x_i + b_{y_i}}}{\sum_{j=1}^{n} e^{W_j^T x_i + b_j}} \tag{7}$$

where $x_i \in \mathbb{R}^d$ is the ith feature that belongs to the y_ith class. y_i has four classes, that is, normal baseline (NB), inner race fault (IRF), ball fault (BF), and outer race fault (ORF). And

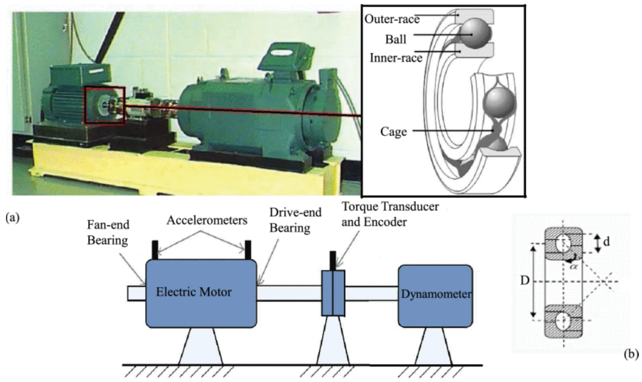

FIGURE 5. (a) An Experimental platform of the CWRU [25] bearing components, and (b) its cross-sectional view. (Original image taken from [26]).

$W \in \mathbb{R}^{d\times n}$ and $b \in \mathbb{R}^d$ denote the feature dimension, last connected layer and bias term, respectively.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. DATASET AND EXPERIMENTAL SETTING

1) CWRU DATASET

Some experiments are performed on one of the popular bearing dataset CWRU [25] dataset. CWRU [25] dataset was created by Case Western Reserve University. Rolling element bearings, known as bearings, are vulnerable components in the machinery whose health condition. The rolling element bearing has four components: inner-race, outer-race, ball, and cage, as shown in Figure 5, which shows the experimental platform of the CWRU.

CWRU [25] data has one normal baseline condition (NB) and three fault conditions, e.g. inner race fault (IRF), ball fault (BF), and outer race fault (ORF). Each condition has 4 different motor speeds, 1797RPM, 1772RPM, 1750RPM, and 1730RPM respectively. In terms of fault conditions, there are also different fault diameters and different sampling frequencies. Because some fault conditions miss some data. For simplicity, experiments are performed on the signal with a 12k sampling frequency and 0.007 inches, and pick centered outer race as outer race fault (ORF). In the experiment, the signals of 1797RPM, 1772RPM, and 1750RPM are set as training data, and 1772RPM as speed template. For the testing, an unknown speed 1730RPM is set as test data, as shown in Table 1.

TABLE 1. Experimental setting on CWRU dataset.

Training Motor Speed : Rounds/min (RPM)		Test Speed (Unknown)
Source Speed	Target Speed	
1797, 1772, 1750	1772	1730

2) MULTI-SPEED DATASET

In order to evaluate the effectiveness of the proposed method in the condition of large changes of speed, a rolling bearing dataset is built which has multiple

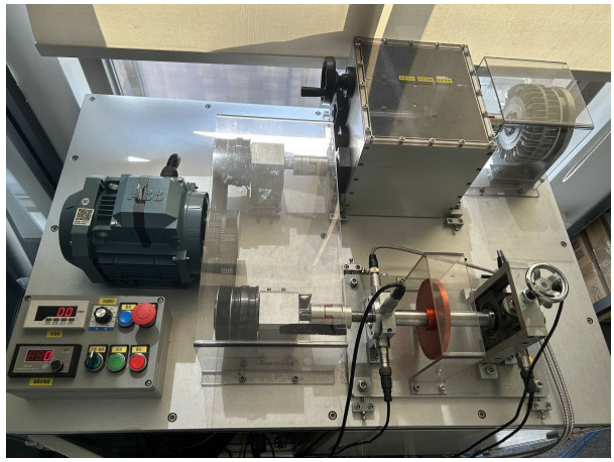

FIGURE 6. Multi-Speed rolling bearing data collection experiment equipment.

different rotational speeds in the experimental equipment. The experimental platform is shown in Figure 6. This multi-speed dataset has 5 different motor speeds, that is 400RPM, 600RPM, 800RPM, 1000RPM and 1200RPM. Compared with the existing dataset, this dataset has larger changes of speed, with 200RPM speed change. To simplify the experiment, this dataset collects 1160 normal signals and 883 signals in the condition of an unbalanced rolling bearing.

To fully evaluate the proposed method in different situations, three test conditions are set, as shown in Table 2. For each condition, there are three speeds as training set, and the rest of the unknown speeds as test set.

B. EXPERIMENTAL ENVIRONMENT AND DATA PROCESSING

In the experimental setup, Python 3.8.5 for its robust ecosystem and PyTorch 1.2.0 for its dynamic neural network building capabilities. The Adam optimizer was employed for network training. This algorithm is favored for its adaptive learning rate properties, which can lead to more efficient convergence in training deep neural networks. A constant learning rate of 0.001 was set for the optimizer. This rate was chosen based on preliminary experiments that indicated it allows for a steady decrease in loss without overshooting the minimum. The computations were carried out on a GPU endowed with 8 GB of memory, providing a suitable environment for the efficient processing of deep learning models.

The DTM model involves noise adding processing, to enhance the generalizability and robustness of model in the context of Rolling Bearing Fault Diagnosis. The diffusion preprocessing pipeline incorporated the augmentation of training data with Gaussian noise. Gaussian noise is a statistical noise that has its magnitude determined according to a normal distribution, a common inherent noise type in real-world sensor data and electronic instrumentation. This noise simulation is pivotal as it closely mirrors the

TABLE 2. Experimental setting on the multi-speed dataset.

Conditions	Training Motor Speed: RPM		Test Speed (Unknown)	Speed Changes between Test & Target
	Source Speed	Target Speed		
Condition 1	400, 800, 1200	800	600, 1000	$\lvert 600-800\rvert = 200, \lvert 1000-800\rvert = 200$
Condition 2	400, 600, 800	600	1000, 1200	$\lvert 1000-600\rvert = 400, \lvert 1200-600\rvert = 600$
Condition 3	800, 1000, 1200	1000	400, 600	$\lvert 400-1000\rvert = 600, \lvert 600-1000\rvert = 400$

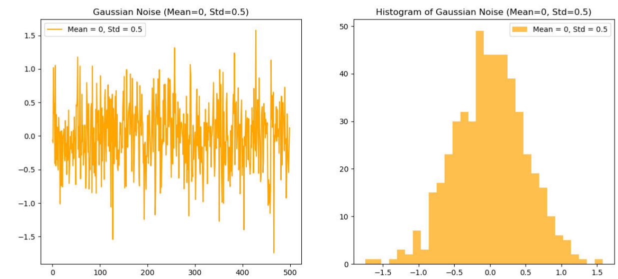

FIGURE 7. Gaussian noise with mean=0, std=0.5.

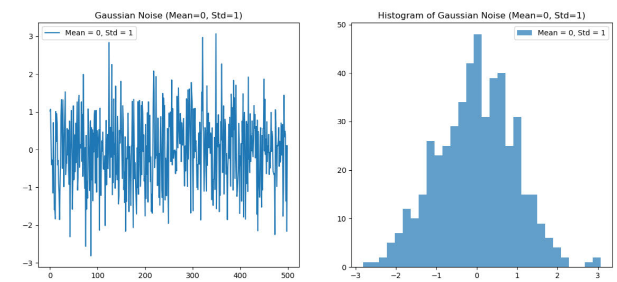

FIGURE 8. Gaussian noise with mean=0, std=1.

operational conditions that rolling bearings are subjected to, which often include random noise from various sources such as vibrations, thermal effects, and electrical interference. Following is the Gaussian noise examples, the first with a mean of 0 and a standard deviation of 1 to replicate typical noise intensity, and the second with a mean of 0 and a standard deviation of 0.5 to emulate scenarios with lower noise levels, as shown in Figure 7 and Figure 8. By training the model to distinguish between the fault signatures and these noise patterns, the model can improve the diagnostic accuracy in diverse and unpredictable real-world environments.

C. VISUALIZATION OF SPEED TRANSFORMATION ON CWRU DATASET

In order to show the effectiveness of DTM treatment in a more intuitive way, the histogram statistics are plotted to show the Euclidean Distances between template speed signal and different speed test signals on the four conditions. The Figure 9 shows the result on the Normal Baseline condition, the Figure 10 shows the result on the Inner Race Fault condition, the Figure 11 shows the result on the Ball the Fault condition, and the Figure 12 shows the result on the Ball the Outer Race Fault condition. The blue histograms represent the Euclidean Distances on the original signals, the red histograms represent the Euclidean Distances on the signals after DMT transformation.

From these figures, it is obvious that the distances between different speed signals on the original signals are large and dispersive. In contrast, the distances between different speed signals after DMT processing are small and concentrative. The blue histograms show that the distances between them are big and spread out. This means the signals are quite different from each other. However, after applying the DTM, shown by the red histograms, these distances become much smaller and grouped closely together. This change is important because it tells us that the DTM is really good at transforming signals of varying speeds into a standard 'template speed.' It shows that the DTM model has the ability which can transfer a signal with different speeds into the signal with template speed. With the assistance of DTM transformation, DTM gets rid of the differences caused by speed and brings out features that don't change with speed. This makes it much easier to spot faults in bearings, even if the machine is running at different speeds.

D. HISTOGRAM STATISTICS OF DIFFERENT HEALTH CONDITIONS ON CWRU DATASET

To show the signals after DTM transformation have a powerful distinguish ability to identify four different healthy conditions. The histograms are plotted to show the Euclidean distances between signals (after DTM transformation) of each pair of conditions. There are four distinct conditions on CWRU data: Normal Baseline, Ball Fault, Inner Race Fault, and Outer Race Fault. The Figure 13 shows the result on the Normal Baseline condition with other conditions, the Figure 14 shows the result on the Ball Fault condition with other conditions, the Figure 15 shows the result on the Inner Race Fault condition with other conditions, and the Figure 16 shows the result on the Outer Race Fault condition with other conditions. The blue histograms represent the Euclidean Distances on the negative pair conditions, the red histograms represent the Euclidean Distances on the positive pair conditions.

A significant variance in distance distributions is observed. Specifically, for pairs of conditions that are not similar (negative pairs), the histograms reveal large and dispersive distances, indicating a clear differentiation between the conditions. Conversely, for similar conditions (positive pairs), the distances are markedly smaller and more concentrated, as evidenced in the histograms. This stark contrast in the distribution of distances underlines the robust capability

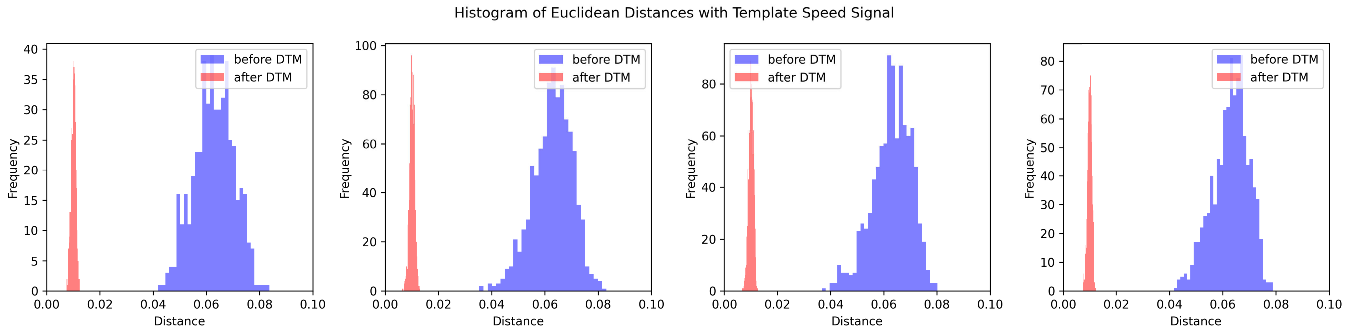

FIGURE 9. **Histogram of euclidean distances between template speed signal (motor speed: 1772 RPM) and test signals. Motor speeds (from left to right) include "known" speeds (1797, 1772, and 1750RPM) and "unknown" speed (1730 RPM) at the normal baseline condition.**

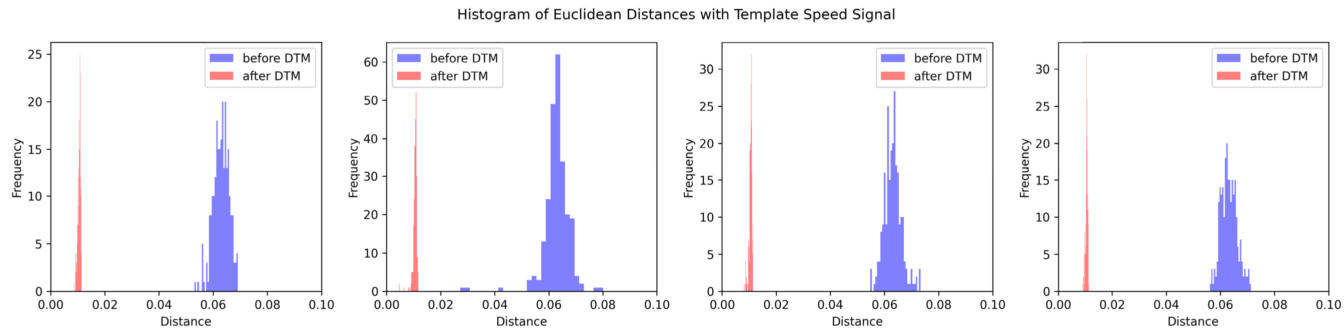

FIGURE 10. **Histogram of euclidean distances between template speed signal (motor speed: 1772 RPM) and test signals. Motor speeds (from left to right) include "known" speeds (1797, 1772, and 1750RPM) and "unknown" speed (1730 RPM) at the inner race fault condition.**

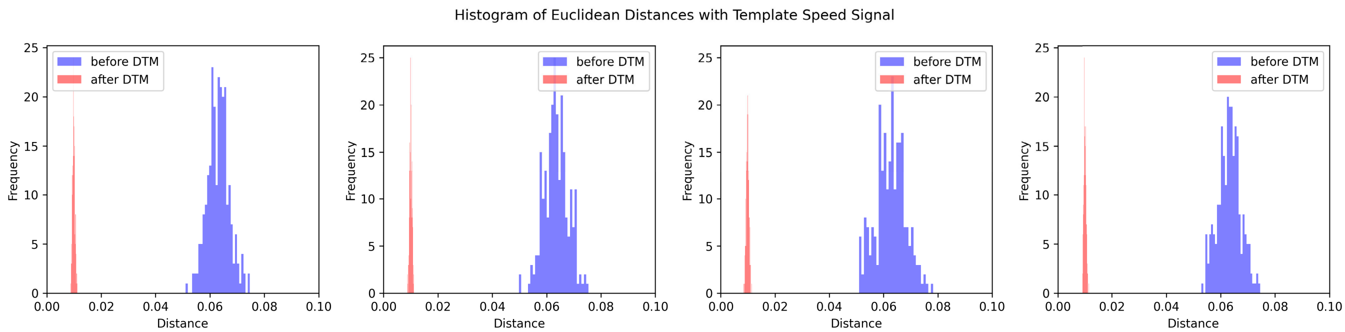

FIGURE 11. **Histogram of euclidean distances between template speed signal (motor speed: 1772 RPM) and test signals. Motor speeds (from left to right) include "known" speeds (1797, 1772, and 1750RPM) and "unknown" speed (1730 RPM) at the ball fault condition.**

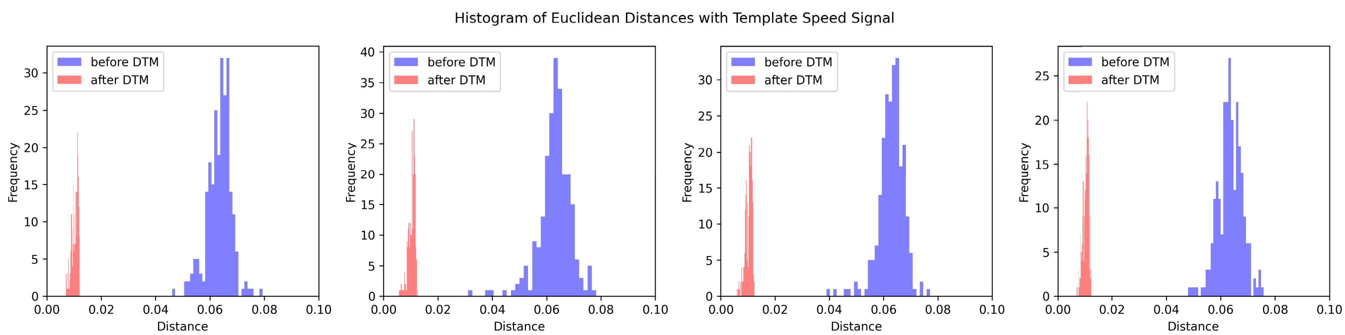

FIGURE 12. **Histogram of euclidean distances between template speed signal (motor speed: 1772 RPM) and test signals. Motor speeds (from left to right) include "known" speeds (1797, 1772, and 1750RPM) and "unknown" speed (1730 RPM) at the outer race fault condition.**

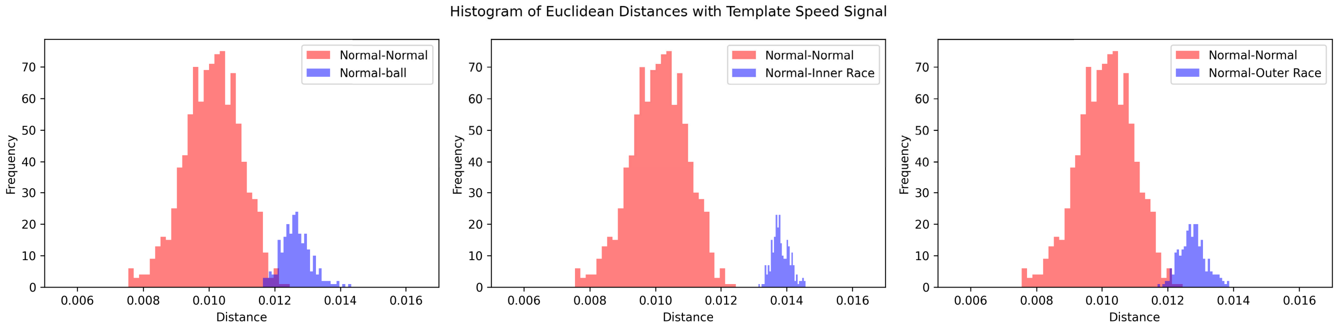

FIGURE 13. **Histogram of euclidean distances between normal template signal and other condition signals (ball fault, inner race fault, outer race fault).**

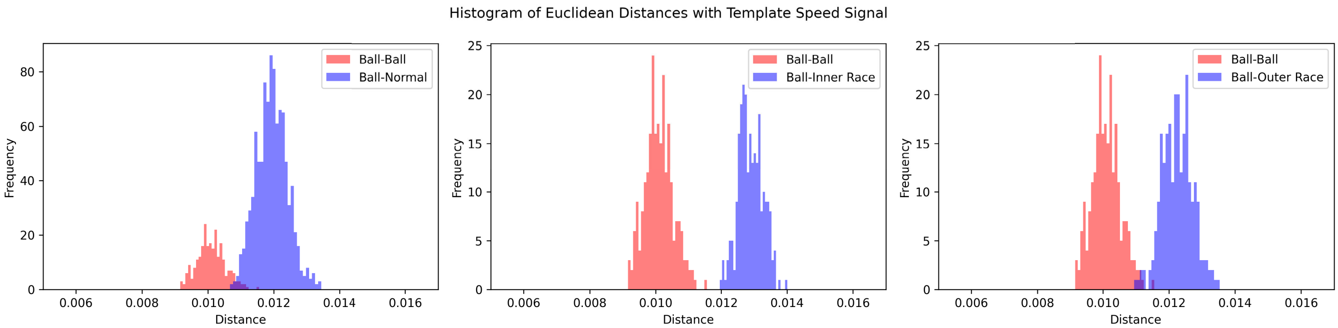

FIGURE 14. **Histogram of euclidean distances between ball fault template signal and other condition signals (normal baseline, inner race fault, outer race fault).**

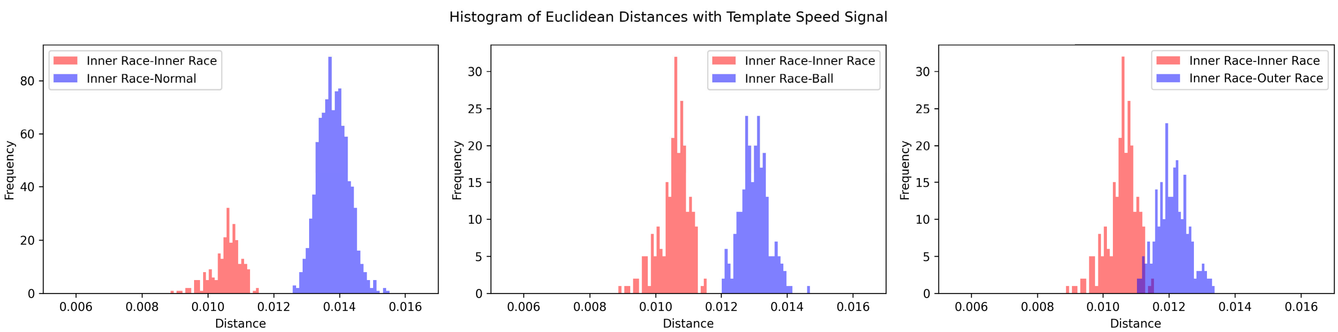

FIGURE 15. **Histogram of euclidean distances between inner race fault template signal and other condition signals (normal baseline, ball fault, outer race fault).**

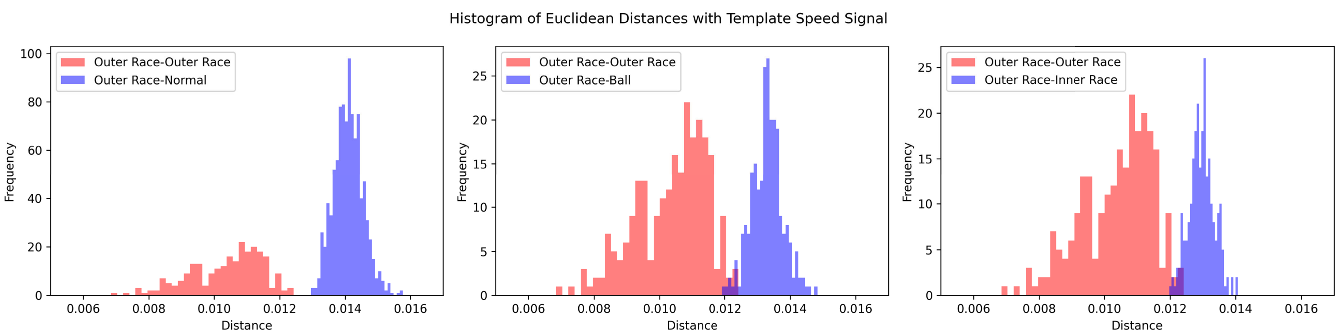

FIGURE 16. **Histogram of euclidean distances between outer race fault template signal and other condition signals (normal baseline, ball fault, inner race fault).**

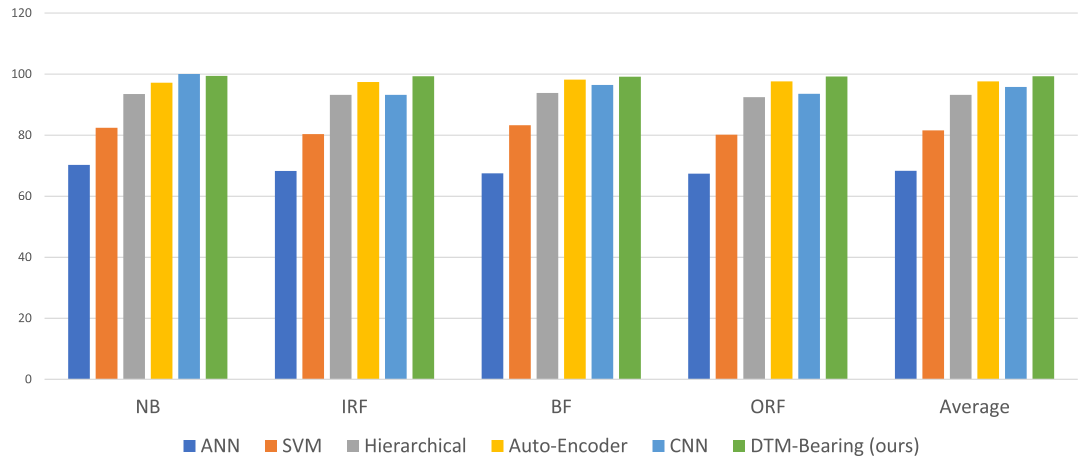

FIGURE 17. **Comparison with other methods. *DTM-Bearing* is ours, it achieves the highest performance on average accuracy compared with other methods.**

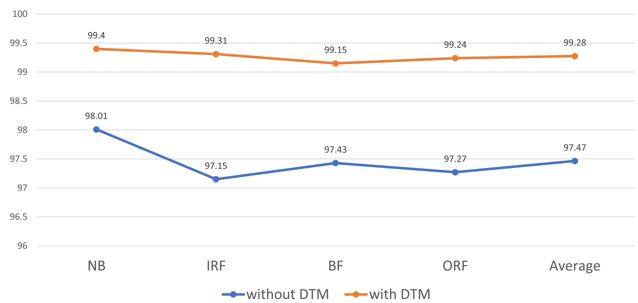

FIGURE 18. **Comparison analysis of the classification accuracies of Diffusion Transformation Model (with DTM) vs. without Diffusion Transformation Model (without DTM).**

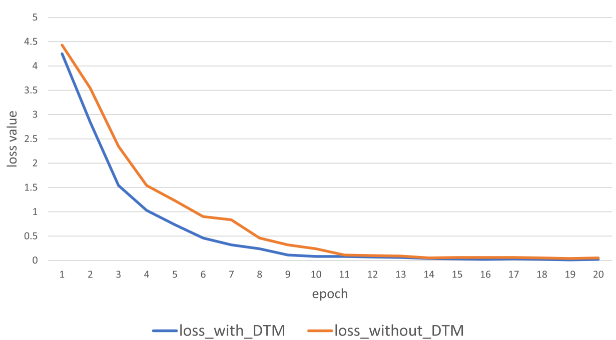

FIGURE 19. **Comparison of the learning curve of Diffusion Transformation Model (with DTM) vs. without Diffusion Transformation Model (without DTM).**

of the after DTM transformation to distinguish effectively among the four different health conditions. The histogram analysis thus not only validates the discriminative power of the feature but also provides a quantifiable means to assess the severity and type of bearing faults, a critical aspect in predictive maintenance and fault diagnosis. By looking at how these distances group in different conditions, it can understand and identify each fault type better. This shows that the proposed way of measuring is really good at telling these four conditions apart.

E. EFFECTIVENESS OF DTM ON CWRU DATASET

The experimental result of the proposed method can be seen in Figure 18. There are 4 accuracies, including the accuracy of normal baseline condition (NB), inner race fault (IRF), ball fault (BF) and outer race fault (ORF). The average accuracy of *DTM-bearing* can achieve 99.28 %.

In order to show the effectiveness of the Diffusion Transformation Model (DTM), the experiment without DTM network is performed, the experimental result of without-DTM can also be seen in Figure 18. From Figure 18, it can see the overall performance will be increased when adding the module of DTM. The average accuracy increases from 97.47% to 99.28%. It is obvious shows that the Diffusion Transformation Model (DTM) is a feasible way to improve the performance of bearing fault diagnosis.

The learning curve of above without-DTM and with-DTM frameworks during training can be seen in Figure 19. It is clear that with the loss value with DTM framework can be more accelerate convergence and reduce overall loss value during the training process.

Here, the emphasis lies in highlighting that the proposed framework can improve the accuracy of bearing fault diagnosis, even when trained with only three different speeds. With the increase in the number of vibration rotation speed signals in the training stage, the proposed framework can further facilitate the performance of bearing fault diagnosis. According to the research of popular transformation model [10], [27], the accuracy gap can be improved more if put signals with more different rotation speeds into the training process. This is because it can provide a much denser sampling and learn its relations to lighten the burden of speed-invariant feature extraction.

F. COMPARISONS WITH OTHER METHODS ON CWRU DATASET

To validate the performance of the proposed method *DTM-Bearing*, this paper compares the proposed *DTM-Bearing* model with other methods on the task of bearing fault

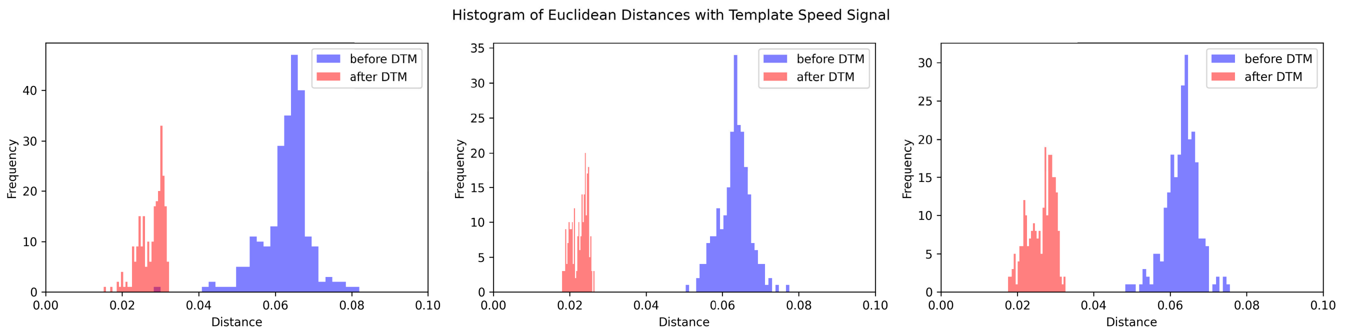

FIGURE 20. Histogram of euclidean distances between template speed signal (motor speed: 800 RPM) and test signals. ("known" motor speed from left to right: 400, 800, and 1200 RPM) at the normal baseline condition.

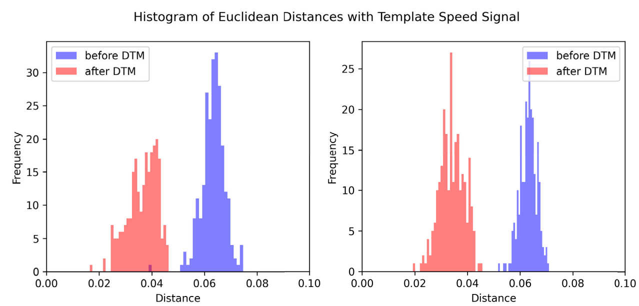

FIGURE 21. Histogram of Euclidean Distances between template speed signal (motor speed: 800 RPM) and test signals ("unknown" motor speed from left to right: 600 and 1000 RPM) at the Normal Baseline condition.

diagnosis, including some recent deep learning methods, such as based on transfer learning and neural networks method CNN [5], hierarchical convolutional network based method Hierarchical [6], and ensemble deep Auto-Encoder [7] method. In addition, the proposed *DTM-Bearing* approach also compares with some of the traditional machine learning methods, such as ANN [5] and SVM [2]. The comparison result can be seen in Figure 17.

It is very clear that the accuracy of *DTM-Bearing* is much better than that of traditional machine learning methods (ANN [5] and SVM [2]) in the fault detection of inner race fault (IRF), ball fault (BF), and outer race fault (ORF). In terms of deep learning methods [5], [6], [7], it can be noticed that *DTM-Bearing* achieves the highest average accuracy compared with these methods.

G. VISUALIZATION OF SPEED TRANSFORMATION ON MULTI-SPEED DATASET

In order to show the effectiveness of DMT model on the large change speed dataset. The histograms are plotted to show the Euclidean Distances between the template signal and test signals. For the multi-speed dataset, there are five speeds, (400, 600, 800, 1000, and 1200 RPM. 800 RPM is set as the target speed. The "known" speeds (400, 800, and 1200 RPM) are utilized for training, while the "unknown" speeds (600 and 1000 RPM) are reserved for testing.

The Figure 20 and Figure 21 show the result of "known" speeds and "unknown" speeds on the normal condition, respectively. For these two figures, it is obvious that following DTM processing, these distances become markedly smaller and more concentrated both "known" speeds and "unknown" speeds conditions.

The Figure 22 and Figure 23 show the result of "known" speeds and "unknown" speeds on the unbalanced fault condition, respectively. They have same pattern with normal condition. These visualizations reveal a striking contrast: the distances between different speed signals in their original form are large and highly dispersed. However, following DTM processing, these distances become markedly smaller and more concentrated. It shows again that DTM can convert signals of varying speeds to a uniform, template speed. This capability is critical for extracting speed-invariant characteristics, which significantly enhances the robustness of fault diagnosis across diverse vibration speed conditions.

H. HISTOGRAM STATISTICS OF DIFFERENT HEALTH CONDITIONS ON MULTI-SPEED DATASET

The histograms of Euclidean distances between signals (after DTM transformation) of each pair of health conditions are plotted. There are two health conditions on multi-speed dataset: normal and unbalanced fault condition. The Figure 24 shows the result on the normal template signal with unbalanced fault test signal, while Figure 25 shows the result on the unbalanced template signal with normal test signal. From these figures, it shows that the DTM's powerful ability to distinguish between different health states of the bearing system effectively. This distinction in histogram patterns highlights the model's potent diagnostic capabilities, offering a reliable means of identifying and differentiating various health conditions within bearings.

I. PERFORMANCE ON MULTI-SPEED DATASET

According to the setting of Table 2. The experiments are performed on the multi-speed dataset. The experimental result of three conditions is shown in Figure 26. From Figure 26, it is clear that the highest accuracy is on condition 1, even if the speed change between the test signal and target signal achieves 200 RPM. In terms of condition 2 and condition 3, the speed change between the test signal and target signal achieves 400 RPM and 600 RPM, the

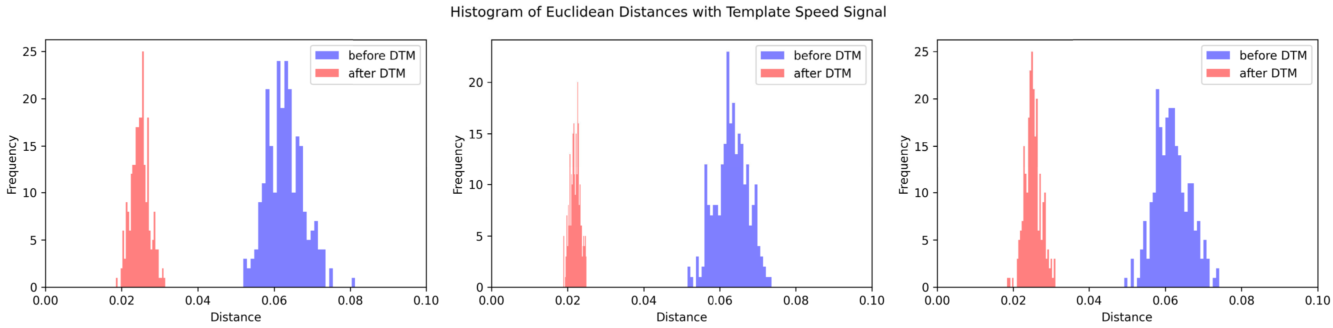

FIGURE 22. **Histogram of euclidean distances between template speed signal (motor speed: 800 RPM) and test signals. ("known" motor speed from left to right: 400, 800, and 1200 RPM) at the unbalance condition.**

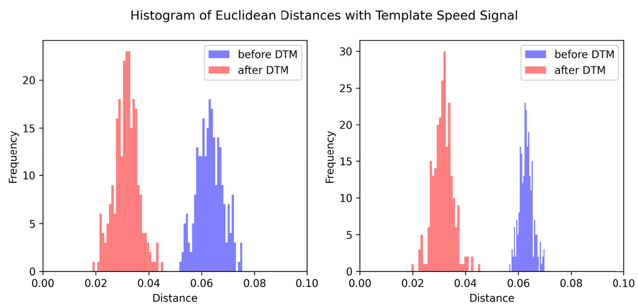

FIGURE 23. **Histogram of euclidean distances between template speed signal (motor speed: 800 RPM) and test signals ("unknown" motor speed from left to right: 600 and 1000 RPM) at the unbalanced condition.**

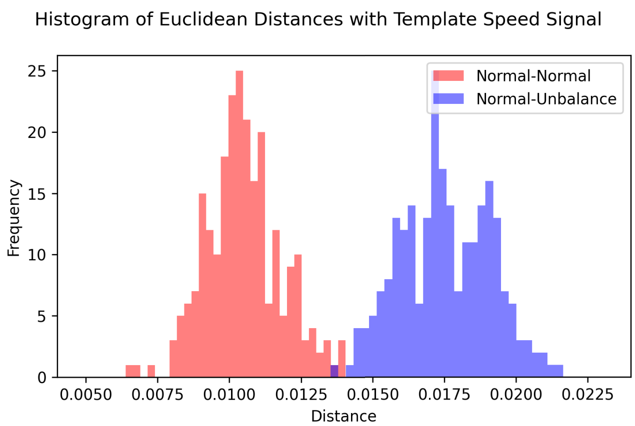

FIGURE 24. **Histogram of euclidean distances between normal template signal and unbalanced fault signal.**

accuracy of the proposal can still be more than 98%. It is obvious shows that the proposed *DTM-bearing* framework is an effective way to improve the robustness of rotation speed variations.

J. COMPARISON WITH DIFFERENT GENERATIVE MODELS

This paper's two main contributions are the transformation strategy and diffusion model network. In order to show the usefulness of transformation strategy and diffusion model network on the bearing fault diagnosis. Experiments are performed on three different generative models, that is, Variational AutoEncoders (VAEs) [13], Generative Adversarial Networks (GANs) [16], and Diffusion Model [19]. The experiment setting is following Table 2 condition 1.

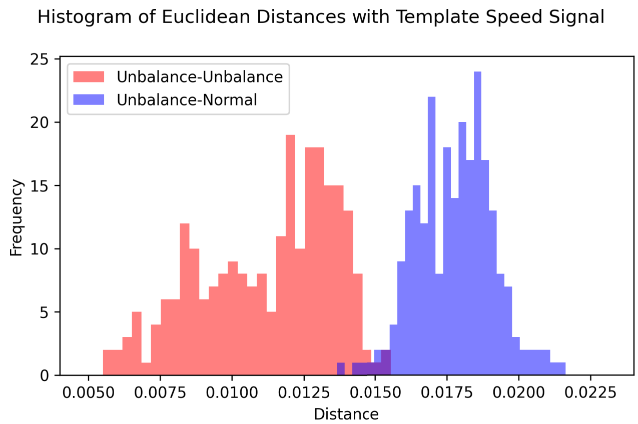

FIGURE 25. **Histogram of euclidean distances between unbalanced template signal and normal fault signal.**

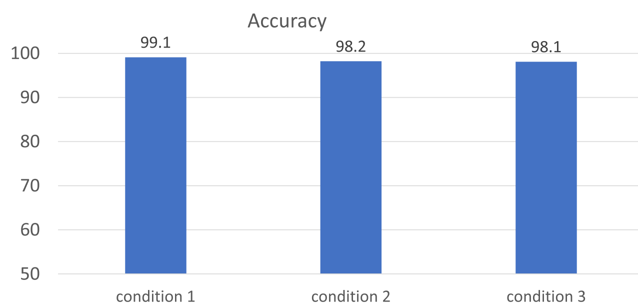

FIGURE 26. **The performance on the three conditions (Table 2).**

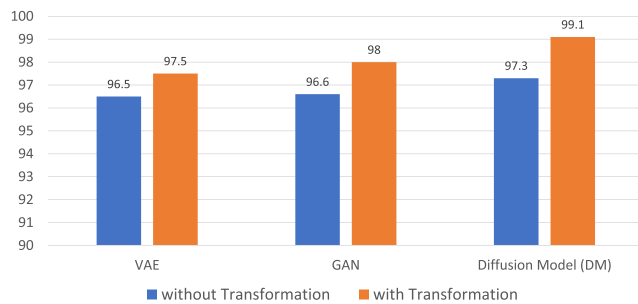

FIGURE 27. **Comparison of different generative models.**

Each generative model has two strategies, one is without a transformation strategy, another one is with a transformation strategy. The experimental results as shown in Figure 27. From Figure 27, it is clear that the Diffusion Model performs best performance compared with VAEs and GANs in the area of bearing fault diagnosis. In addition, the overall performance of with transformation strategy can further be increased both VAEs, GANs and Diffusion Model networks.

V. CONCLUSION AND FUTURE WORK

This paper introduces the *DTM-Bearing* framework, aimed at enhancing bearing fault diagnosis by minimizing variations in vibration speed and extracting consistent features. Through experiments, the effectiveness of the *DTM-Bearing* framework in bolstering the accuracy of diagnosing bearing faults across different vibration speeds is demonstrated.

To the best of our knowledge, the method presented here represents the first amalgamation of diffusion and transformation concepts for bearing fault diagnosis. Future plans involve expanding the *DTM-Bearing* framework to encompass other sources of variation. In bearing fault diagnosis, variations don't solely stem from vibration speed; they can also originate from different components of the bearing (such as the fan-end or drive-end) and varying sampling frequencies. The comprehensive nature of the *DTM-Bearing* framework offers researchers a potential avenue to address these diverse sources of variation, fostering innovative solutions in bearing fault diagnosis.

The broad scope of the *DTM-Bearing* framework holds promise for substantial advancements in the field of bearing fault diagnosis. Its inclusive approach signifies a significant milestone, setting the stage for future progress and breakthroughs in this area.

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