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GENERATIVE ADVERSARIAL NETWORK FOR CLASSIFICATION OF MECHANICAL FAULT DIAGNOSIS MODEL

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Abstract. The scarcity and imbalance of annotated fault data pose significant challenges to the reliability of intelligent industrial diagnostics. To address this issue, we propose an integrated fault diagnosis framework based on multi-domain feature fusion and generative adversarial networks (GANs). Unlike traditional approaches that treat generation and classification as independent stages, our model unifies these two processes. This method achieves diagnosis by transforming raw vibration signals into multi-domain representations (time domain, frequency domain, and time-frequency domain). The core innovation lies in the restructured generator architecture: a Transformer encoder captures global signal correlations, combined with an Efficient Channel Attention (ECA) mechanism for adaptive recalibration of feature weights, ensuring high-fidelity sample synthesis. Additionally, the model employs a dual-function discriminator that distinguishes genuine from synthetic samples while directly performing multi-class fault classification. Extensive experiments on CWRU and JNU benchmark datasets demonstrate that this approach surpasses existing state-of-the-art algorithms, achieving superior performance in Structural Similarity (SSIM), Peak Signal-to-Noise Ratio (PSNR), and diagnostic accuracy. This end-to-end solution effectively mitigates data scarcity challenges in industrial settings.

Keywords: fault diagnosis, generative adversarial networks, limited data, supervised learning, time-series analysis

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ГЕНЕРАТИВНО-СОСТЯЗАТЕЛЬНАЯ СЕТЬ ДЛЯ КЛАССИФИКАЦИИ МОДЕЛИ ДИАГНОСТИКИ МЕХАНИЧЕСКИХ НЕИСПРАВНОСТЕЙ

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Аннотация. Нехватка и несбалансированность аннотированных данных о неисправностях создают серьезные проблемы для надежности интеллектуальной промышленной диагностики. Для решения этой проблемы мы предлагаем интегрированную систему диагностики неисправностей, основанную на слиянии многодоменных характеристик и генеративных состязательных сетях (GAN). В отличие от традиционных подходов, которые рассматривают генерацию и классификацию как независимые этапы, наша модель объединяет эти два процесса. Этот метод позволяет проводить диагностику путем преобразования необработанных сигналов вибрации в многодоменные представления (временная область, частотная область и временная-частотная область). Основная инновация заключается в реструктурированной архитектуре генератора: кодер Transformer улавливает глобальные корреляции сигналов в сочетании с механизмом Efficient Channel Attention (ECA) для адаптивной перекалибровки весов признаков, обеспечивая высокую точность синтеза образцов. Кроме того, модель использует дискриминатор с двойной функцией, который отличает подлинные образцы от синтетических, одновременно выполняя многоклассовую классификацию неисправностей. Обширные эксперименты на эталонных наборах данных CWRU и JNU демонстрируют, что этот подход превосходит существующие современные алгоритмы, достигая превосходных результатов по структурному сходству (SSIM), пиковому отношению сигнал/шум (PSNR) и точности диагностики. Это комплексное решение эффективно смягчает проблемы нехватки данных в промышленных условиях.

Ключевые слова: диагностика неисправностей, генеративно-состязательные сети, ограниченные данные, контролируемое обучение, анализ временных рядов

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Introduction

As was stated in our previous article [22], with the rapid advancement of Industry 4.0, the demand for the health monitoring and operational stability of intelligent industrial equipment has significantly increased. As core components of rotating machinery, the condition of rolling bearings directly impacts the safety and stability of industrial systems. Due to their operation under variable speed and load conditions, bearings are susceptible to a variety of faults [22].

Traditional fault diagnosis methods typically rely on the analysis of 1D vibration signals from sensors, requiring professionals to manually extract and assess signal features before designing classifiers. Although these approaches have achieved high accuracy, they are often time-consuming and labor-intensive, rendering them ill-suited for the automated, intelligent diagnostic requirements of modern manufacturing systems [22].

In recent years, data-driven methodologies, particularly convolutional neural networks (CNNs), have emerged as powerful tools for capturing nonlinear fault characteristics without human intervention. However, the efficacy of these deep learning models is often contingent upon the availability of massive, annotated datasets. In practical industrial settings, acquiring high-quality fault data is challenging, leading to issues of data paucity and class imbalance. Consequently, standard models frequently fail to generalize or maintain high diagnostic accuracy when training samples are scarce [6, 7].

To mitigate the challenges of data scarcity, generative adversarial networks (GANs) [8] have been adopted as a robust strategy for data augmentation. By synthesizing realistic fault samples, GANs can rebalance datasets and enhance model robustness [9]. It is important to note that while our previous research explored the use of improved vision transformers (ViT) as standalone classifiers for fault diagnosis [22], the current study focuses on a different architectural approach. Specifically, rather than relying on an external ViT classifier, this work aims to optimize the generative process itself to produce higher fidelity samples for an integrated diagnostic framework.

The primary objective of this research is to develop a deep learning framework tailored for bearing fault diagnosis under severely limited data conditions. We propose an integrated model that fuses multi-domain features (time, frequency and time-frequency). Distinct from prior approaches, the novelty of this model lies in its generator architecture, which incorporates a Transformer encoder to capture global signal interactions and an Efficient Channel Attention (ECA) mechanism to refine feature representation.

The core challenge addressed in this study is the generation of high-fidelity synthetic data to compensate for the lack of training samples. By strategically mixing original and generated data, we aim to construct an extended, balanced dataset that serves as the foundation for highly accurate fault classification performed directly by the model's integrated discriminator.

The specific contributions of this paper are summarized as follows:

1. **Investigation of data scarcity:** We conduct a systematic evaluation of bearing fault diagnosis performance under conditions of limited and unbalanced training samples using public datasets.

2. **Novel data enhancement model:** We develop a multi-domain feature fusion GAN. This model uniquely integrates features from three domains and utilizes adversarial learning with attention mechanisms to ensure the generation of synthetic data that closely mimics the physical properties of real fault signals.

3. **Performance benchmarking:** We perform a comprehensive comparative analysis against state-of-the-art algorithms. The experimental results validate that the proposed method achieves superior reliability and applicability for industrial fault diagnosis tasks.

Related works

Traditional and deep learning-based fault diagnosis methods

Bearing fault diagnosis techniques have evolved from traditional statistical methods to advanced methods based on deep learning. Traditional methods, such as Gaussian Mixture Models (GMMs) and Hidden Markov Models (HMMs), rely heavily on hand-extracted features, such as Mel Frequency Cepstral Coefficients (MFCCs), for modeling speech features. However, these methods have limited performance in dealing with high-dimensional data and complex working conditions.

With the rise of deep learning, models such as CNN, recurrent neural networks (RNNs) and long-short-term memory networks (LSTMs) are widely used in fault diagnosis. These models can automatically learn the hierarchical features of the original vibration signals, improving the accuracy and robustness of fault identification.

In [20], a transformer-based conditional generative adversarial network migration learning model was proposed, which enhances the quality and diversity of the generated data by introducing sample labeling information, thus improving the performance of cross-domain fault diagnosis.

In [21], a bearing fault diagnosis study based on a multimodal approach combined with a multi-scale time-frequency and statistical feature fusion model was proposed, which is able to better handle non-stationary and nonlinear vibration data.

Limitations

Although the above methods have made significant progress in bearing fault diagnosis, there are still some challenges. Traditional methods have limited performance in dealing with high-dimensional data and complex working conditions, while deep learning methods face problems such as high consumption of computational resources and strong dependence on a large amount of labeled data.

Rationale for GAN

GANs provide a compelling solution to key challenges in bearing fault diagnosis, especially data scarcity and class imbalance. By introducing an adversarial framework between the generator and the discriminator, GANs can learn complex data distributions and synthesize real fault samples to expand limited data sets. This is particularly important in industrial environments where access to labeled fault data is costly or impractical. The generator captures subtle fault features-often from the time, frequency, or time-frequency domain-while the discriminator ensures sample quality through adversarial training. This dynamic change not only improves the robustness of diagnostic models, but also enhances their generalizability to real-world scenarios. Thus, GANs are a promising direction for building more accurate and resilient fault diagnosis systems under constrained data conditions.

Materials and methods

This study analyzes various bearing operating states using the Case Western Reserve University (CWRU) dataset [10]. This dataset provides information on the vibration characteristics of bearings in different states including normal operation, inner ring, outer ring and ball damage.

Fig. 1 shows a schematic of a bearing including the main structural elements: inner ring, outer ring and balls. Damage can be associated with different surface areas or different defect sizes, resulting in differences in bearing operating conditions. These differences create a complex classification problem that requires the use of deep learning techniques to accurately diagnose faults.

Data preprocessing involves converting vibration signals into multimodal representations, which allows the consideration of time, frequency, and time-frequency characteristics for further analysis and model training.

In the CWRU dataset, bearing damage is categorized by type and location of occurrence. The main categories include: ball damage, inner ring damage, outer ring damage, and normal condition. Additionally, damage is differentiated by diameter, which is represented by values of 0.007, 0.014, 0.021 etc. Thus, by combining the different types of damage and their diameters, the operational condition of bearings can be divided into ten categories.

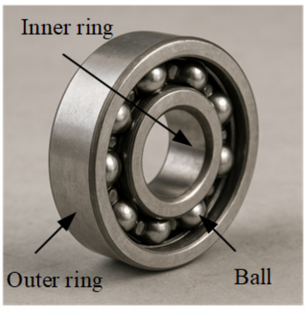

Fig. 1. Bearing diagram

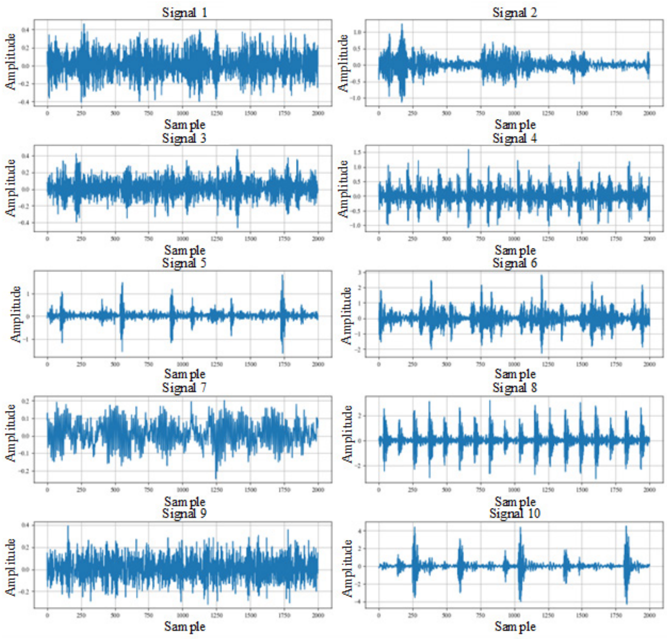

Fig. 2. Vibration signals of bearings in different damage states

In general, bearing vibration signals recorded under different operating conditions have markedly different characteristics, as evidenced by the data presented in Fig. 2. For example, in the range from sample 0 to sample 1000, signal 2 exhibits almost no pronounced vibration, while the vibration of signal 8 has a distinctly periodic character.

Furthermore, in the range from sample 200 to sample 1200, there is a significant difference in the vibration amplitudes of signal 1 and signal 9. These differences illustrate the complexity of analyzing bearing condition data and confirm the need for methods capable of efficiently processing and analyzing data with such variations.

As shown in Fig. 3, in order to obtain a complete set of vibration signal characteristics, this study used a time domain data transformation approach to transform the data into different representations.

The sample data were transformed in three different domains:

1. Time domain – the original signals in their original form.
2. Frequency domain – transforming the data using Fast Fourier transform (FFT) to reveal the frequency components of the signal.
3. Time-frequency domain – a representation obtained using a time-frequency domain transform, such as the Short-time Fourier transform (STFT), which allows you to analyze the dynamics of frequency components over time.

This approach provides a comprehensive analysis of signal characteristics, which is a key step for successful model training and bearing fault diagnosis.

Design of bearing fault diagnostic modeling

To address the persistent challenges of bearing fault diagnosis under data-constrained and imbalanced conditions, this study introduces a unified, end-to-end deep learning framework. Unlike our previous work [22], which relied on an external classifier coupled with a generative model, the approach proposed in this study orchestrates sample generation and fault diagnosis within a single, cohesive architecture. As illustrated in Fig. 4, the framework is designed to synthesize high-fidelity multi-domain samples while simultaneously executing precise 10-category fault diagnosis through an integrated mechanism.

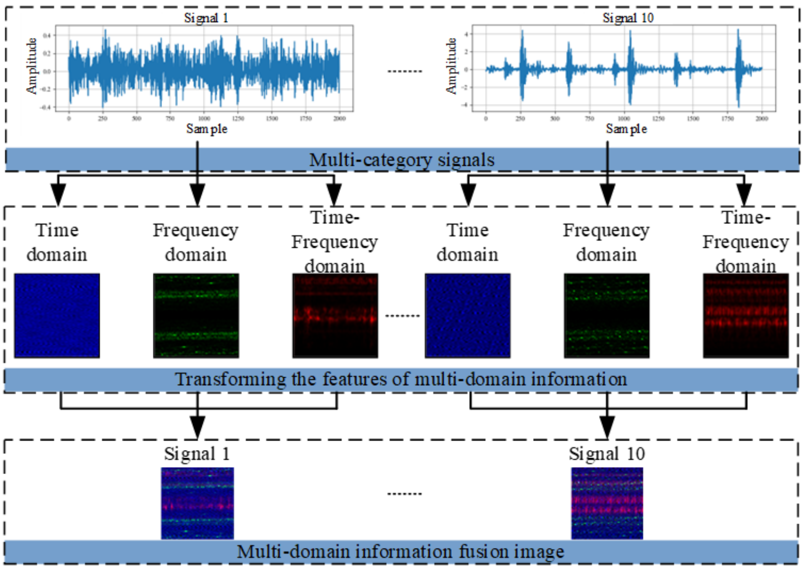

Fig. 3. Information about vibration signals in time, frequency and frequency-time domains

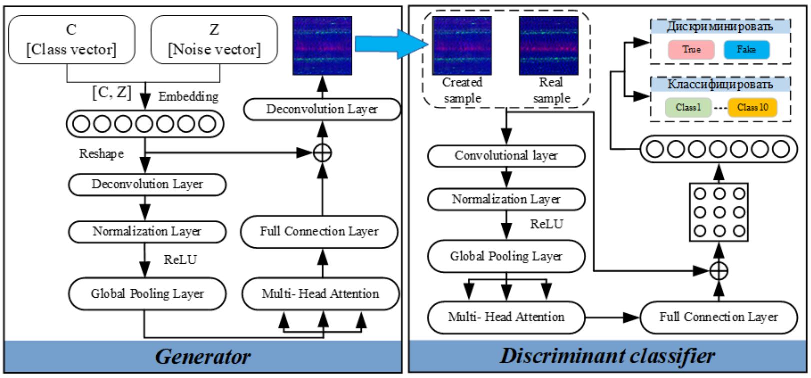

Fig. 4. Proposed fault diagnosis model

Optimization of hyperparameters is pivotal for ensuring model convergence and diagnostic reliability. Through empirical validation, the framework employs an Adam optimizer initialized with a learning rate of 0.001. Training is conducted with a batch size of 128 over 6000 epochs to guarantee stable feature extraction and distribution matching.

The primary function of the generator is to map latent noise distributions into interpretable, multi-domain signal representations. The generative process is initiated by fusing two distinct input vectors:

– Latent Vector (Z): A noise vector sampled from a standard Gaussian distribution to induce sample diversity.

– Label Embedding (C): A category-specific vector projected into a high-dimensional space via an embedding layer to condition the generation.

Mathematically, the embedding transformation is governed by the weight matrix:

$$\mathbf{W}_{\text{embed}} \in \mathbb{R}^{n_{\text{classes}} \times d_{\text{embed}}}, \tag{1}$$

where n_{class} represents the number of fault categories and d_{embed} denotes the embedding dimension. The vectors Z and C are fused via element-wise multiplication and subsequently reshaped into a four-dimensional tensor, serving as the foundational input for the deep deconvolutional layers.

To capture long-range dependencies within the feature maps $X \in \mathbb{R}^{B\times C\times H\times W}$, a Transformer-based enhancement module is embedded within the generator. Initially, spatial information is compressed into a channel descriptor Y via Global Average Pooling (GAP):

$$Y_c = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W} X_{c,i,j}, \tag{2}$$

where c denotes the channel index, while H and W represent spatial dimensions. The resulting channel descriptor Y_c is flattened into a sequence to facilitate processing by the Multi-Head Attention (MHA) mechanism [7]. The MHA module dynamically models inter-channel correlations by computing Query (Q), Key (K), and Value (V) matrices through learned linear projections:

$$\text{head}_i = f_{\text{softmax}}\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right)V_i; \tag{3}$$

$$\text{MHA}(Q,K,V) = \text{Concat}(\text{head}_1,\ldots,\text{head}_h)W, \tag{4}$$

where d_k is the dimension of the attention heads, h is the number of heads, and $W \in R^{D\times D}$ is the linear projection matrix. This mechanism allows the generator to contextualize local features within the global signal structure. Prior to attention computation, a Normalization Layer (NL) is applied to stabilize gradients:

$$Y' = NL\big(Y + \text{MultiHead}(Q,K,V)\big), \tag{5}$$

where Y and Y' represent the embedding sequence and MHA output, respectively, and $NL(\cdot)$ denotes the normalization operation.

To further refine feature saliency, an ECA mechanism is integrated. The ECA module adaptively recalibrates channel weights, emphasizing informative features while suppressing noise. The re-weighted feature output $\mathbf{O}_{\text{ECA}}$ is computed as:

$$\mathbf{O}_{\text{ECA}} = \sigma(\mathbf{Y}')\cdot\mathbf{X}, \tag{6}$$

where $\sigma(\cdot)$ denotes the sigmoidal activation function and $\mathbf{O}_{\text{ECA}}$ is the output feature after weighting the channel attention.

A defining characteristic of this framework is the dual-function discriminator. Distinct from methods that utilize separate downstream classifiers (e.g., [22]), the discriminator in this model is engineered to directly perform multi-class fault diagnosis alongside its adversarial duties.

The discriminator loss function consists of two components: classification loss and category classification loss. For real samples S_{real}, the loss for real samples $S_{D,\text{real}}$ is defined as:

$$L_{D,\text{real}} = -\mathbb{E}_{S_{\text{real}}\sim P_{\text{data}}}\left[\log D(S_{\text{real}})\right] + \mathbb{E}_{y_{\text{real}}}\left[\log P\big(y = y_{\text{real}} \,\big|\, S_{\text{real}}\big)\right], \tag{7}$$

where y_{real} represents the true label.

For S_g generated samples, the generated loss $L_{D,\text{fake}}$ is defined as:

$$L_{D,\text{fake}} = \mathbb{E}_{z\sim P_z}\left[\log D\left(S_g\right)\right] - \mathbb{E}_{y_\text{gen}}\left[\log P\left(y = y_\text{gen}\left|S_g\right.\right)\right], \tag{8}$$

where y_gen denotes the generated label.

To improve the robustness of training, a Gradient Penalty (GP) term is introduced:

$$L_\text{GP} = \lambda_\text{GP}\cdot\mathbb{E}_{\hat{S}\sim P_S}\left[\left(\left\|\nabla_{\hat{S}} D\left(\hat{S}\right)\right\|_2 - 1\right)^2\right], \tag{9}$$

where P_S is the uniform sampling distribution between real and generated samples, and λ_GP is the regularization parameter. Therefore, the total discriminator loss is expressed as:

$$L_D = L_{D,\text{real}} + L_{D,\text{fake}} + L_\text{GP}. \tag{10}$$

The task of the generator is to fool the discriminator while ensuring that the generated samples are assigned the correct class labels. The generator loss function is defined as:

$$L_\text{G} = -\mathbb{E}_{z\sim P_z}\left[\log D\left(S_g\right)\right] + \mathbb{E}_{y_\text{gen}}\left[\log P\left(y = y_\text{gen}\left|S_g\right.\right)\right]. \tag{11}$$

The fault classification model achieves accurate recognition of different fault modes by supervised learning and is optimized using a loss function based on cross entropy. To further improve the performance of the model, the real and generated data are combined for training. The loss function of the fault classification model is defined as:

$$L_{total} = \min_G \max_D \left(L_D + L_G\right). \tag{12}$$

Results and discussion

In order to evaluate the model's ability to generate data, this paper uses a joint sample quality assessment method to evaluate the performance of the generated samples. The method includes PSNR and SSIM [12, 13, 22].

PSNR measures the total pixel error between the generated image and the original image. PSNR is calculated as follows:

$$\text{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x_{ij} - y_{ij}\right)^2; \tag{13}$$

$$\text{PSNR} = 20\cdot\log_{10}\left(\frac{I_\text{MAX}}{\sqrt{\text{MSE}}}\right), \tag{14}$$

where MSE is the mean square error; M and N are the width and height of the image, respectively; X_{ij} and Y_{ij} are the pixel values of the original and generated images, respectively; I_MAX is the maximum possible pixel value.

SSIM evaluates the perceptual similarity between the generated image and the original image. Its formula is as follows:

$$\mathrm{SSIM}(x,y)=\frac{\left(2\mu_x\mu_y+C_1\right)\left(2\sigma_{xy}+C_2\right)}{\left(\mu_x^2+\mu_y^2+C_1\right)\left(\sigma_x^2+\sigma_y^2+C_2\right)}, \tag{15}$$

where μ_x and μ_y are the mean values of the two images; μ_x^2 and μ_y^2 are their variance; σ_{xy} is the covariance of the two images, respectively; C_1 and C_2 are constants to ensure computational stability.

Fig. 5 shows the variation of the training loss of the proposed model and the validation accuracy of the discriminator. From it, it is evident that the adversarial training of the generator and discriminator gradually stabilizes after 1000 epochs. The discriminator accuracy is also close to 100%.

The Figs. 6 and 7 show the quality scores of different models for each category of generated samples, including GAN [8], ACGAN [14], DCGAN [15] and the method used in this paper. Comparing the histograms for each category shows that the method proposed in this paper outperforms its counterparts in terms of average SSIM and PSNR and ranks first in all ten categories.

In addition, the difference between the SSIM and PSNR scores for each category is only ±0.02, indicating the high stability and accuracy of the model in training the features in all categories. These results confirm that the proposed method can effectively meet the challenge of generating high-quality data and contribute to the improvement of bearing fault diagnosis.

To further validate the effectiveness of the proposed classification method, we compared the developed model with various state-of-the-art classification models including Random Forest (RF) [16], Support Vector Machine (SVM) [17], Hierarchical CNN (H-CNN) [18], 2D-CNN [19] and the method proposed in this paper. The results of the comparative analysis are presented in Fig. 8.

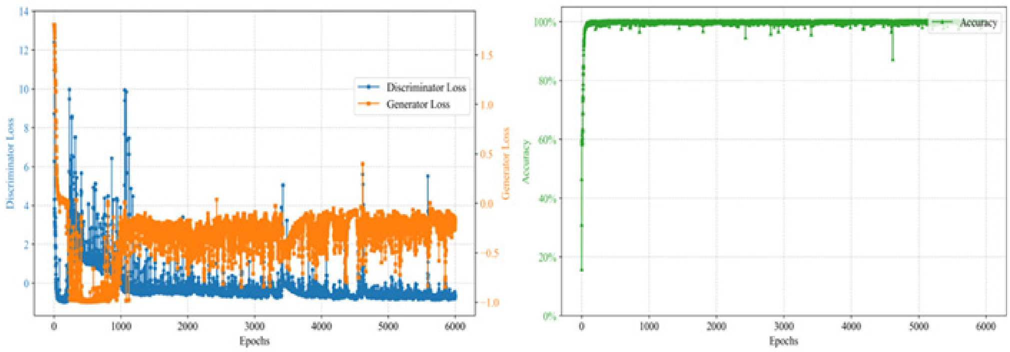

Fig. 5. Variation of losses during model training and discriminator validation accuracy

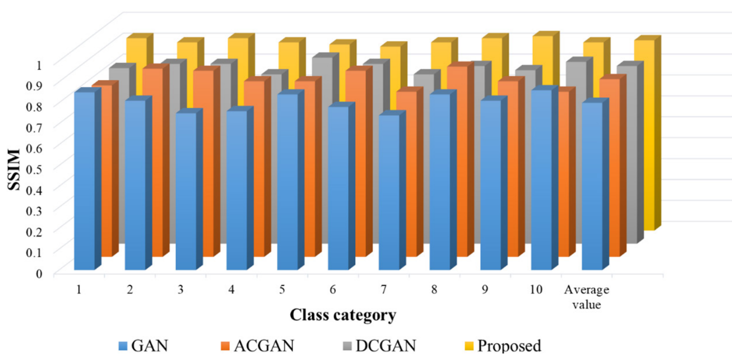

Fig. 6. Comparison of SSIM with different generation models

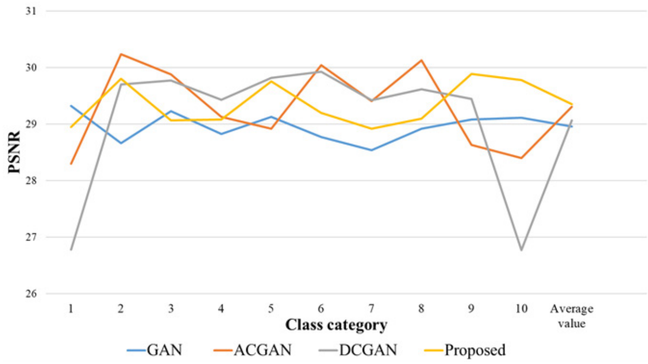

Fig. 7. Comparison of PSNR with different generation models

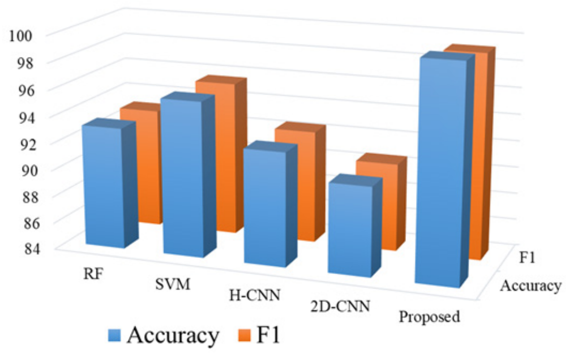

Fig. 8. Comparison of accuracy and F1 between different models

These results demonstrate the superiority of the proposed model in bearing fault diagnosis tasks, especially under conditions of limited and unbalanced data. On key classification metrics, the proposed method consistently outperforms alternative approaches, confirming its robustness and practical applicability.

Among machine learning models, the random forest and support vector machine algorithms show similar results, with classification accuracies of 93.13% and 95.63%, and F1-scores of 93.01% and 95.60%, respectively. Although SVM outperforms RF processing of high-dimensional data, its performance in the task of fault signal classification remains limited. This is due to the inherent weaknesses of traditional methods in extracting features and adapting them to high-dimensional data, which does not fully reveal the underlying features of the signals.

Among deep learning models, the method proposed in this paper demonstrates the highest performance on all metrics. The classification accuracy reaches 99.91% and the F1-score reaches 99.25%. These metrics emphasize the significant advantages of the developed model for fault classification tasks. The generation of high-quality augmented data using the proposed approach significantly improves the generalization ability and classification performance of the model, unlocking its full potential in complex diagnosis tasks.

To deeply evaluate the classification performance of the proposed model on the CWRU bearing dataset, this paper conducts relevant experiments and constructs a confusion matrix based on the test set samples to clearly demonstrate the model's ability to recognize different types of faults. Fig. 9 shows the confusion matrix, where the horizontal axis shows the fault types predicted by the model and the vertical axis shows the actual fault types. As can be seen from Fig. 9, the proposed model achieves

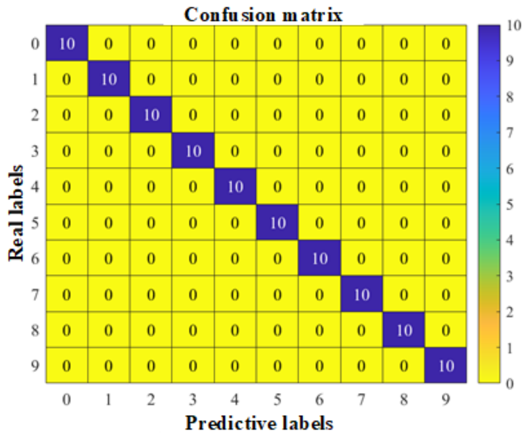

Fig. 9. Confusion matrix results

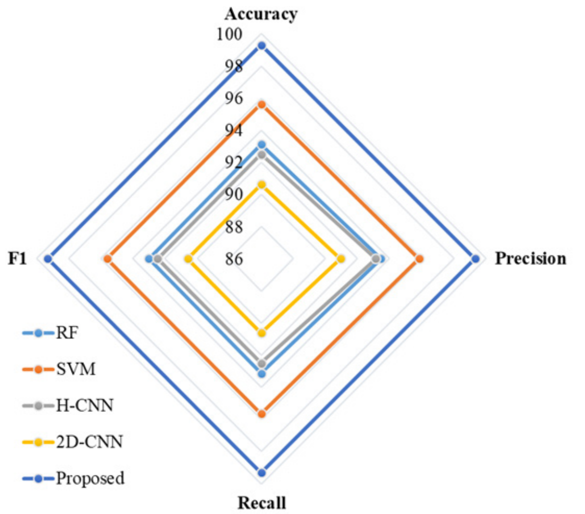

Fig. 10. The radar plot of data comparison with models

high classification accuracy of ten fault types in the CWRU dataset, which fully confirms its effectiveness and robustness in fault diagnosis tasks.

In addition, this paper further verifies the bearing data from Jinan University. In this paper, we classify the signal data in different operating conditions, and there are eight kinds of bearing data. The comparison of experimental data with different comparison models is shown in Fig. 10.

As can be seen from the data distribution graph in Fig. 10, the method proposed in this paper outperforms the compared methods in terms of accuracy, predictive value, recall and F1-score, which proves the strong generalization ability of the proposed method.

In addition, in order to verify the generalization ability of the proposed model in this paper, experiments are conducted on the JNU dataset, and the experimental results of the comparison models are shown in Fig. 11. As can be seen from the figure, the proposed model exhibits the best diagnostic results.

In summary, the experiments on CWRU and JNU datasets show that the model proposed in this paper is effective in diagnosing the operating conditions under different mechanical conditions.

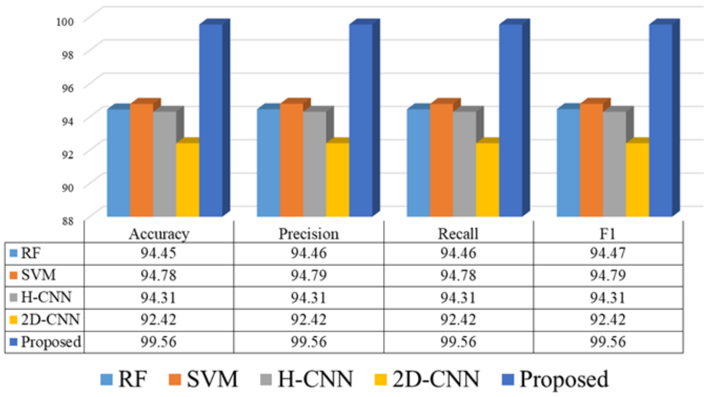

Fig. 11. Comparing the results of the model on the JNU dataset

Conclusion

This study presents a novel deep learning-based approach for bearing fault diagnosis, tailored to address the data scarcity and diagnostic complexity characteristic of the industry 4.0 context. By integrating an enhanced GAN with a multi-domain feature fusion framework, the proposed method effectively augments limited datasets and improves diagnostic performance. The key findings are summarized as follows:

- Data augmentation: The improved GAN demonstrates superior capability in generating high-fidelity samples, as evidenced by higher PSNR and SSIM values compared to conventional data generation methods.
- Multi-domain feature learning: By leveraging temporal, frequency, and time-frequency domain features, and enhancing them through attention mechanisms, the model achieves robust and comprehensive feature representation.
- Superior classification accuracy: The proposed model achieves a diagnostic accuracy of 99.91%, significantly outperforming established baselines such as SVM and 2D-CNN.

Overall, this work contributes to the advancement of intelligent diagnostic systems by providing a scalable and generalizable solution. Future research may explore extending the framework to multi-task learning scenarios and applying it to other complex industrial systems for enhanced prognostic capabilities.

REFERENCES

1. **Buinosov A.P., Vasiliev V.A., Baitov A.S., Ivanov A.I.** Bench testing of algorithms for diagnosing rolling bearings of the on-board diagnostic system and forecasting the service life of the main and auxiliary components of the MCRSU. *Herald of the Ural State University of Railway Transport*, 2021, Vol. 51, No. 3, Pp. 40–49. DOI: 10.20291/2079-0392-2021-3-40-49

2. **Gerike P.B., Yeshcherkin P.V.** Development of a unified diagnostic criterion for mining shovel power-mechanical equipment rolling bearings' diagnosis. *Vestnik nauchnogo tsentra po bezopasnosti rabot v ugol'noi promyshlennosti* [*Bulletin of the Scientific Center for Safety in the Coal Industry*], 2020. No. 2, Pp. 65–72.

3. **Xu X., Yang X., He C., Shi P., Hua C.** Adversarial domain adaptation model based on LDTW for extreme partial transfer fault diagnosis of rotating machines. *IEEE Transactions on Instrumentation and Measurement*, 2024, Vol. 73, Art. no. 3538811. DOI: 10.1109/TIM.2024.3476708

4. **Huang F., Zhang K., Zheng Q., Li Z., Lai X., Ding G., Zhao M.** An open-set method for diagnosing unknown bogie bearing faults using a hybrid open score relation network. *IEEE Transactions on Instrumentation and Measurement*, 2024, Vol. 73, Art. no. 3539211. DOI: 10.1109/TIM.2024.3480217

5. **Triandofilidi I., Kotsyuba I.Yu.** Prediction the operating state of an electric vehicle charging station using neural networks. *Modern High Technologies*, 2024, No. 4, Pp. 101–106. DOI: 10.17513/snt.39978

6. **Romanovskaya Y.M., Ilyushin E.A.** Sound augmentation methods. *International Journal of Open Information Technologies*, 2023, Vol. 11, No. 3, Pp. 12–18.

7. **Ibryaeva O.L., Mohammad M.N.** Fault diagnosis of rolling bearings using spectral peaks and neural networks. *Bulletin of the South Ural State University. Series: Computational Mathematics and Software Engineering*, 2022, Vol. 11, No. 2, Pp. 59–71. DOI: 10.14529/cmse220205

8. **Goodfellow I., Pouget-Abadie J., Mirza M., Xu B., Warde-Farley D., Ozair S., Courville A., Bengio Y.** Generative adversarial networks. *Communications of the ACM*, 2020, Vol. 63, No. 11, Pp. 139–144. DOI: 10.1145/3422622

9. **Uzkikh G.I.** Application of generative adversarial networks (GANs) in image processing. *Vestnik nauki* [*Science Herald*], 2024, Vol. 77, No. 8 (4), Pp. 182–185.

10. **Zou Y., Zhao W., Liu Y., Zhang Z.** Research on rolling bearing fault diagnosis method based on the combination of optimized VMD and BP neural network. *Bulletin of PNU*, 2023, Vol. 70, No. 3, Pp. 41–56.

11. **Vaswani A., Shazeer N., Parmar N., Uszkoreit J., Jones L., Gomez A.N., Kaiser L., Polosukhin I.** Attention is all you need. *arXiv:1706.03762*, 2017. DOI: 10.48550/arXiv.1706.03762

12. **Lian J., Yang Z., Liu J., Sun W., Zheng L., Du X., Yi Z., Shi B., Ma Y.** An overview of image segmentation based on pulse-coupled neural network. *Archives of Computational Methods in Engineering*, 2021, Vol. 28, Pp. 387–403. DOI: 10.1007/s11831-019-09381-5

13. **Guo C., Lian J., Kang Y., Zheng L., Zhang M.** The limited-FCMSPCNN algorithm for image defogging. *Journal of Physics: Conference Series*, 2021, Vol. 1961, Ar. no. 012024. DOI: 10.1088/1742-6596/1961/1/012024

14. **Odena A., Olah C., Shlens J.** Conditional image synthesis with auxiliary classifier GANs. *Proceedings of the 34th International Conference on Machine Learning*, 2017, Vol. 70, Pp. 2642–2651. DOI: 10.5555/3305890.3305954

15. **Radford A., Metz L., Chintala S.** Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv:1511.06434*, 2015. DOI: 10.48550/arXiv.1511.06434

16. **Paul A., Mukherjee D.P., Das P., Gangopadhyay A., Chintha A.R., Kundu S.** Improved random forest for classification. *IEEE Transactions on Image Processing*, 2018, Vol. 27, No. 8, Pp. 4012–4024. DOI: 10.1109/TIP.2018.2834830

17. **Cervantes J., Garcia-Lamont F., Rodríguez-Mazahua L., Lopez A.** A comprehensive survey on support vector machine classification: Applications, challenges and trends. *Neurocomputing*, 2020, Vol. 408, Pp. 189–215. DOI: 10.1016/j.neucom.2019.10.118

18. **Zhu X., Bain M.** B-CNN: Branch convolutional neural network for hierarchical classification. *arXiv:1709.09890*, 2017. DOI: 10.48550/arXiv.1709.09890

19. **Bird J.J., Faria D.R., Manso L.J., Ayrosa P.P.S., Ekárt A.** A study on CNN image classification of EEG signals represented in 2D and 3D. *Journal of Neural Engineering*, 2021, Vol. 18, No. 2, Art. no. 026005. DOI: 10.1088/1741-2552/abda0c

20. **Li X., Ma J., Wu J., Li Z., Tan Z.** Transformer-based conditional generative transfer learning network for cross domain fault diagnosis under limited data. *Scientific Reports*, 2025, Vol. 15, Art. no. 6836. DOI: 10.1038/s41598-025-91424-y

21. **Chen H., Li S., Lu X., Zhang Q., Zhu J., Lu J.** Research on bearing fault diagnosis based on a multimodal method. *Mathematical Biosciences and Engineering*, 2024, Vol. 21, No. 12, Pp. 7688–7706. DOI: 10.3934/mbe.2024338

22. **Guo C., Potekhin V.V., Li P., Kovalchuk E.A., Lian J.** MDFT-GAN: A multi-domain feature transformer GAN for bearing fault diagnosis under limited and imbalanced data conditions. *Applied Sciences*, 2025, Vol. 15, Art. no. 6225. DOI: 10.3390/app15116225

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