CGAN based data generation for process monitoring*

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***Abstract*— The normal data are sampled from the industrial process far more than fault data. Due to the existence of unbalanced data, the traditional learning method are difficult to classify the fault correctly. This paper designs a generation network to effectively augment the fault data and obtain the balanced industrial dataset. Conditional Generative Adversarial Network (CGAN) is constructed to generate a large amount of new fault data which has similar distribution with the original real fault data. The time series data are first transform into matrix format in order to adapt the input of CGAN. Then convolutional neural network (CNN) is used for fault diagnosis. The proposed method is applied in an actual gas-solid fluidized bed equipment to verify its effectiveness.**

I. INTRODUCTION

The complexity of the industrial process is constantly expanding with the increasing of production scale. The fault detection and diagnosis have great significance for the long-term safe and stable operation [1]. In general, the fault diagnosis methods are divided into three categories: mathematical model based, artificial intelligence based and data-driven methods [2]. Accurate mathematical models are often difficult to obtain due to the process complexity which limits its industrial application. Artificial intelligence based methods, such as fuzzy logic, causal analysis and expert systems, do not require detailed mathematical models, but need a large amount of production experience and process knowledge, so the versatility is poor. Data driven diagnosis methods use the sampling historical data to mine the different features or modes between the normal and fault operations. It has become the most popular method due to its convenience and effectiveness with the development of data sampling, storage and learning technology.

The data quality directly determines the effectiveness of data-driven fault diagnosis method. When it is applied to actual industrial production, there are still many issues should be considered, such as the scarcity of fault samples and the inherent imbalance in fault data distribution [3]–[5]. It inevitably results in the unbalanced phenomenon between different data categories, and cause misclassification when using the traditional deep learning methods for fault diagnosis. The most straightforward way to deal with the unbalanced problem is to construct a balanced dataset [6]. From the data level, the undersampling and oversampling techniques are used to balance data [7], [8], including deleting samples of the majority categories or adding more samples to the minority categories. The representative algorithms include synthetic minority oversampling technique (SMOTE) [9], adaptive synthetic sampling approach (ADASYN) [10], and Borderliner-SMOTE algorithm. However, undersampling may lose data information because it only uses a specific part of samples, and oversampling may cause over-fitting problems due to the repeated data acquisition.

In order to balance the normal data and fault data, many samples are reconstructed which have the similar feature distribution as the original samples. The sample reconstruction can enrich the fault samples and improve the performance of the fault diagnosis. The traditional data reconstruction methods generate synthetic data, such as support vector machine [11], k-nearest neighbor algorithm (KNN) for local interpolation and random forest algorithm (RF) for ensemble-based resampling. They ensure the robust minority class representation. Generative adversarial networks (GAN) launched a research boom since 2014 has been becoming the most popular solution to generate completely new data based on the game of generator and discriminator [12]. Although GAN has been regarded as a milestone in deep learning domain, it often faces pattern collapse, instability and poor robustness. Then the improved variants are proposed such as the deep convolutional generative adversarial network (DCGAN) [13], [14], conditional variational generative adversarial network (CVAE-GAN) [15], conditional generative adversarial network (CGAN) [16], Wasserstein generative adversarial networks (WGAN) [17]. Since CGAN precisely controls the properties of generated content by introducing additional conditional information. Therefore, this paper chooses CGAN to generate new fault data that is similar to the original real fault data distribution.

This paper aims to solve the issues of unbalanced learning based on CGAN to generate more new fault data, and further improve the accuracy of fault diagnosis. Firstly, reconstruct the original fault data with multiple matrix construction methods, such as Toeplitz and Hankel; then CGAN are applied to generate new fault samples based on the reconstructed matrices. The generated fault samples are fed into the original date to balance dataset. Finally, the proposed method is evaluated on an actual gassolid fluidized bed reactor to verify its effectiveness.

The remainder of this paper is organized as follows. Section 2 introduces the ralated principles of matrix reconstruction and diagnosis methodology. Section 3 provides the overall framework and the implementation steps. The

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experiment design and results are explained in Section 4. Section 5 draws conclusions.

II. METHODOLOGY

A. Matrix Reconstruction

Process measured data are time series that usually are difficult to directly input the traditional deep learning model, since the traditional model are often developed for image data. So we first transform the time series to matrix format for later CGAN learning. Assume that the n samplings from the i-th sensor in the original data is $\begin{pmatrix} x_1^i & x_2^i & \dots & x_n^i \end{pmatrix}$. The superscript i represents the number of sensor, and the subscript n represents the number of sampled data.

1) Reshape: The original $1 \times n$ data is reshaped in a certain order to obtain $m \times m$ matrix as follows,

$$\begin{pmatrix} x_1^i & x_2^i & \cdots & x_m^i \\ x_{m+1}^i & x_{m+2}^i & \cdots & x_{2m}^i \\ \vdots & \vdots & \vdots & \vdots \\ x_{m^2-m+1}^i & x_{m^2-m+2}^i & \cdots & x_{m^2}^i \end{pmatrix}_{m\times m} \tag{1}$$

2) Symmetrical Toeplitz: The original measurement value x_n^i is taken as the elements both in the first row and the first column in the Symmetrical Toeplitz matrix transformation, and the remaining measurements are arranged in the upper left corner to form a symmetric matrix,

$$\begin{pmatrix} x_1^i & x_2^i & \cdots & x_m^i \\ x_2^i & x_1^i & \cdots & x_{m-1}^i \\ \vdots & \vdots & \vdots & \vdots \\ x_m^i & x_{m-1}^i & \cdots & x_1^i \end{pmatrix}_{m\times m} \tag{2}$$

3) Asymmetrical Toeplitz: The first row of Asymmetrical Toeplitz matrix is $\begin{pmatrix} x_1^i & x_2^i & \dots & x_m^i \end{pmatrix}$, $\begin{pmatrix} x_1^i & x_{m+1}^i & \dots & x_{2m-1}^i \end{pmatrix}$ as the first column vector, as shown follows,

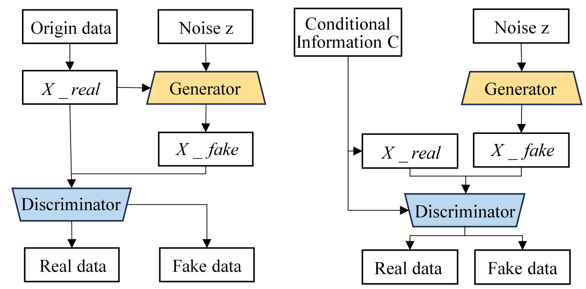
$$\begin{pmatrix} x_1^i & x_2^i & \cdots & x_m^i \\ x_{m+1}^1 & x_1^1 & \cdots & x_{m-1}^1 \\ \vdots & \vdots & \vdots & \vdots \\ x_{2m-1}^i & x_{2m-2}^i & \cdots & x_1^i \end{pmatrix}_{m\times m} \tag{3}$$

4) Asymmetrical Hankel: The sampled measurements $\begin{pmatrix} x_1^i & x_2^i & \dots & x_{2m-1}^i \end{pmatrix}$ is sequencely arranged in the Asymmetrical Hankel matrix,

$$\begin{pmatrix} x_1^i & x_2^i & \cdots & x_m^i \\ x_2^i & x_3^i & \cdots & x_{m+1}^i \\ \vdots & \vdots & \vdots & \vdots \\ x_m^i & x_{m+1}^i & \cdots & x_{2\times m-1}^i \end{pmatrix}_{m\times m} \tag{4}$$

B. CGAN Data generation

The traditional generative adversarial network (GAN) consists of two parts: the generator and the discriminator. The generator is mainly used to learn the real distribution to assure the generated data by more realistic. The discriminator makes a true and false judgment on the generated data. The adversarial learning process is regarded as a game between the generator and the discriminator. Two networks finally reach a dynamic equilibrium: the data generated by the generator approximates the real data distribution, and the its discriminant probability is about 0.5. The schematic diagram of GAN is shown in Fig. 1 (a).



(a) GAN (b) CGAN

Fig. 1: Framework of adversarial learning

GAN have shown remarkable success in generating realistic data, but it suffers from several limitations. One major issue is the lack of control over the generated outputs, since it generates data randomly without specific guidance. This can lead to mode collapse, where the generator produces limited varieties of samples. Additionally, GAN often struggle with training instability and convergence issues. Conditional GAN (CGAN) address these shortcomings by incorporating additional information, such as class labels or attributes, into both the generator and discriminator. This conditioning allows CGAN to generate data with specific desired characteristics, providing greater control over the output. The key advantage of CGAN lies in their ability to produce targeted and diverse samples, making them more suitable for tasks like image-to-image translation, text-to-image synthesis, and other applications requiring precise control over generated content. This improvement enhances both the stability and applicability of GANs in various domains.

The framework of CGAN is shown in Fig.1 (b). In CGAN, both the generator and discriminator are conditioned on additional information y (e.g., class labels or attributes). The objective function becomes [18]:

$$\begin{aligned} \min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x|y)] + \\ E_{z\sim p_G(z)}[\log(1 - D(G(z|y)|y))], \end{aligned} \tag{5}$$

where $x \sim p_{data}(x)$ is the real data following the real distribution $p_{data}(x)$, $z \sim p_G(z)$ is generated data with the corresponding distribution. y is the conditional information (e.g., a class label or feature vector). $G(z|y)$ generates fake data conditioned on both the noise z and the additional information y. $D(x|y)$ and $D(G(z|y)|y)$ are the discriminator's outputs, representing the probability that x is real and $G(z|y)$ is fake, given the condition y.

The primary distinction between GAN and CGAN lies in the conditioning on y. In CGAN, both the generator and discriminator utilize the additional information y to guide the generation and discrimination processes. This allows CGAN to produce outputs that are not only realistic but also aligned with the specific conditions provided, enabling more controlled and targeted data generation.

C. Statistical evaluation method

This section is to evaluate the generation quality of CGAN dealing with unbalanced data at the perspective of statistics, and further verify the effectiveness. The main statistical indicators are as follows.

Mean: It is an indicator that represents the concentration trend of a set of data. It refers to the sum of all the data divided by the number of sets of data.

$$\mu = \frac{1}{N}\sum_{i=0}^{N-1} x_i, \tag{6}$$

where x_i is the observation, μ is the overall mean, and N is the total number of cases.

Variance: It is used to calculate the difference between each observation and the overall mean.

$$\sigma^2 = \frac{1}{N-1}\sum_{i=0}^{N-1}(x_i-\mu)^2 \tag{7}$$

Mode: The most frequently occurring values in a set of data, expressed as “M”.

Median: A measure of central tendency in statistics that represents the middle value of a dataset when the values are arranged in ascending or descending order. It is particularly useful for describing the center of a distribution, especially when the data contains outliers or is skewed. It is represented as “Me”.

Standard deviation: The square root of the variance, which is the average of the squared differences between each data point and the mean. It quantifies how much the individual data points deviate from the mean of the dataset, providing insight into the spread of the data,

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i-\mu)^2} \tag{8}$$

KL divergence: A measure of how one probability distribution diverges from a second, reference probability distribution. It is widely used in information theory, machine learning, and statistics to quantify the difference between two distributions. It is defined in the case of discrete and continuous random variables, respectively,

$$KL(P \parallel Q) = \sum P(x)\log\frac{P(x)}{Q(x)} \tag{9}$$

$$KL(P \parallel Q) = \int P(x)\log\frac{P(x)}{Q(x)}dx \tag{10}$$

KL divergence is non-negative and asymmetrical, that is $KL(P \parallel Q) \neq KL(Q \parallel P)$.

III. Framework and Implementation

The datasets collected from the process industry are typically imbalanced, with fault data being significantly less abundant than normal data. To address this issue, we generate the synthetic fault data to balance the original dataset. The research methodology is outlined as follows. First, fault data are extracted from the existing industrial dataset. The fault time series data are transformed into matrix formats using four distinct matrix transformation methods: Reshape, Symmetrical Toeplitz, Asymmetric Toeplitz, and Asymmetric Hankel. Subsequently, the reconstructed matrices are converted into image representations through grayscale and normalization processing. Generative algorithms CGAN is employed to generate new synthetic data. The newly generated images are then converted back into time series data using the inverse transformation process. The resulting datasets (in time series format) are subjected to statistical analysis and evaluation. Finally CNN algorithm is used to diagnosis the fault. The overall research framework is illustrated in Fig. 2.

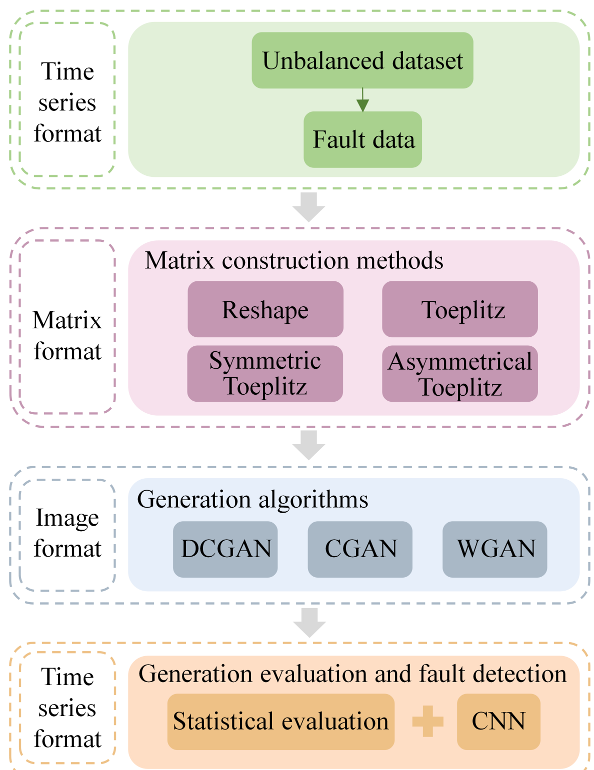


Fig. 2: CGAN based imbalanced fault diagnosis.

IV. Experiment

The proposed method was validated using a polyethylene fluidized bed reactor from Sinopec, as illustrated in Fig. 3. This gas-solid fluidized bed is widely used for ethylene polymerization due to its high mass and heat transfer efficiency, as well as uniform particle mixing, making it ideal for large-scale continuous production. However, operational challenges such as static electricity and inadequate heat removal can lead to particle agglomeration, sheet melting, and eventual reactor shutdown, posing risks of property damage and safety hazards. Thus, accurate fault diagnosis for agglomeration is critical.

Acoustic signals were employed for non-intrusive, real-time monitoring of the fluidized bed. Four acoustic sensors, divided into two pairs, were mounted on the reactor's outer wall. Sensors 1 and 3 were positioned near the distribution plate, while sensors 2 and 4 were placed near the enlarged section. The collected acoustic data were transmitted wirelessly from the MCU in an explosion-proof box to an industrial computer in the control room, enabling continuous monitoring. Data were sampled every 10 seconds, yielding 2,500 datasets from each sensor. The dataset comprises monitoring values from the four sensors during the gas-phase polyethylene production process, providing a robust basis for fault diagnosis.

Fig. 3: Polyethylene fluidized bed reactor.

This experiment aims to evaluate the performance of four matrix construction methods and three generative models. The dataset comprises fault data from January 6 and normal data from April 25. The original time sequence data are shown in Fig. 4, and it can be seen that the original fault data are less than normal data. The obvious fault occurs where the acoustic signal fluctuates greatly. The statistical characteristic are shown in TABLE I. The variance of the original fault data is large than that of the original data, and the value of the fault data is smaller than the normal data as a whole. Fault data have lager maximum and smaller minimum.

The pre-processing stage involves transforming the signal data from sensor 1 into various matrix formats, as shown in Fig. 5. These images serve as intermediate variables and provide valuable insights: darker shades indicate higher values. It offers a visual representation of the data's intensity and distribution.

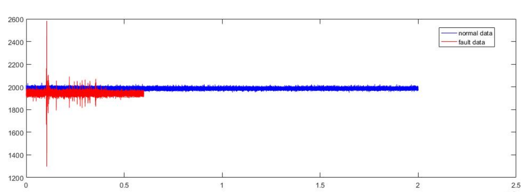
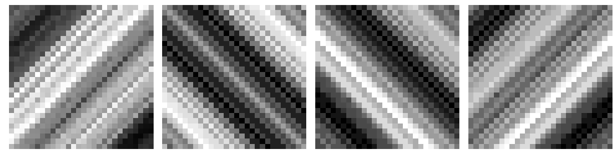


Fig. 4: Original normal and fault time series.

TABLE I: Statistical analysis of original data.

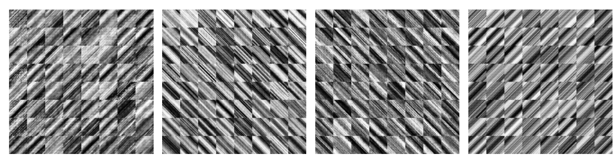
Statistics	Normal data	Fault data
Mean	1.90×10^3	1.94×10^3
Variance	48.17	205.77
Mode	1983	1941
Median	1986	1943
Standard deviation	6.94	14.34



Reshape Sym-Toeplitz Asy-Toeplitz Asy-Hankel

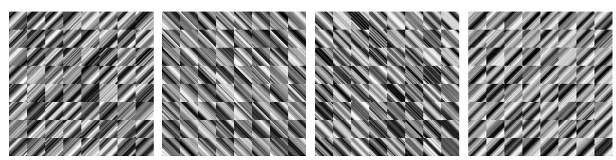
Fig. 5: Data Reconstruction Result.

It gets 10,000 images by these 4 matrix transformations, which are selected as the training dataset of the generation model. CGAN model is trained for 25 epochs with batch size 64. The newly generated images are obtained, containing the same information as the original fault data. Fig. 6-8 show one example of generated fault images from CGAN, DCGAN, and WGAN, respectively.



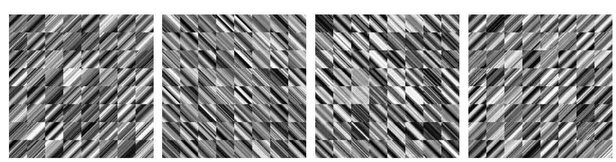
Reshape Sym-Toeplitz Asy-Toeplitz Asy-Hankel

Fig. 6: CGAN generated fault images.



Reshape Sym-Toeplitz Asy-Toeplitz Asy-Hankel

Fig. 7: DCGAN generated fault images.



Reshape Sym-Toeplitz Asy-Toeplitz Asy-Hankel

Fig. 8: WGAN generated fault images.

Fig. 9 is a box plot of the original fault data and fault data generated by different matrix construction methods and different generation models. where 'Fault' stands for the original fault data, 'C', 'DC', and 'W' denote the data generation algorithms CGAN, DCGAN and WGAN, respectively,

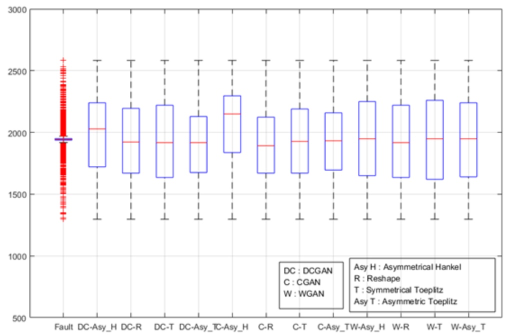


Fig. 9: Box-plot of original and generated fault data.

and 'R', 'T', 'Asy_T', and 'Asy_H' represent the data preprocessing methods of Reshape, Sym_Teoplitz, Asy_Toeplitz, and Asy_Hankel, respectively. From the figure, it is clear that the fault data generated using the time series preprocessing method and the generative models have near maximum and minimum values with the original fault data, and the overall distributions are similar. It shows that the research ideas are feasible in this paper, i.e., the results are reliable using the mapping of the time series data to the image domain through preprocessing and then using the generative models of the image for the generation.

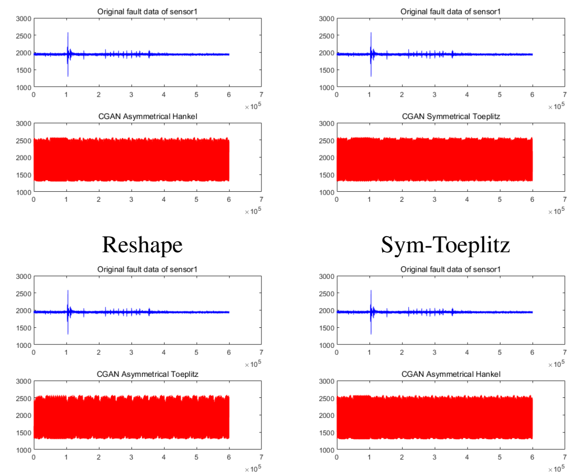
The generated data is statistically evaluated, and the results of CGAN, DCGAN, and WGAN are shown in TABLE II.

TABLE II: Statistical analysis of generative models.

Generation model	Matrix construction	Mean	Variance	Mode	Median	Standard deviation
CGAN	Reshape	1.90×10^3	8.03×10^4	1877	1892	253.43
	Sym_Toeplitz	1.93×10^3	1.00×10^5	1887	1927	316.89
	Asy_Toeplitz	1.92×10^3	8.65×10^4	2003	1932	394.17
	Asy_Hankel	2.05×10^3	9.05×10^4	2306	2149	308.15
DCGAN	Reshape	1.93×10^3	1.05×10^5	1837	1922	323.59
	Sym_Toeplitz	1.93×10^3	1.18×10^5	1927	1917	344.10
	Asy_Toeplitz	1.91×10^3	9.39×10^4	1958	1917	306.51
	Asy_Hankel	1.98×10^3	1.12×10^4	2164	2028	334.82
WGAN	Reshape	1.93×10^3	1.24×10^5	1791	1917	352.46
	Sym_Toeplitz	1.94×10^3	1.34×10^5	2376	1948	365.41
	Asy_Toeplitz	1.94×10^3	1.27×10^5	2069	1948	356.00
	Asy_Hankel	1.95×10^3	1.27×10^5	1932	1948	356.24
Original fault data		1.94×10^3	205.77	1941	1943	14.34

As can be seen from TABLE II, the mean values are close to the original fault data, while the variance and standard deviation are much larger than the original ones for the fault data generated by four data preprocessing methods with C-GAN. The statistics of the data generated after preprocessing with the Asy_Toeplitz matrix construction method are closer to the original fault data than using the other three methods. The distributions between the new samples generated by CGAN and the samples collected directly are much closer to each other. Therefore, CGAN is initially selected as the data generative model.

The inverse transformation of the fake images generated by CGAN is given in Fig. 10. The newly generated fault data focus on the obvious part of the original fault data. It has more faults and more uniform distribution compared with the original fault data, but the maximum and minimum values are similar to the original fault data. However, it is not possible to tell which of four matrix construction methods is better from the figure.



Reshape   Sym-Toeplitz

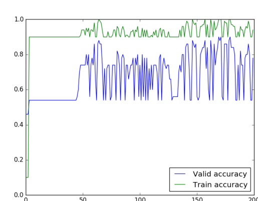
Asy-Toeplitz   Asy-Hankel

Fig. 10: Inverse transformation from the generated data.

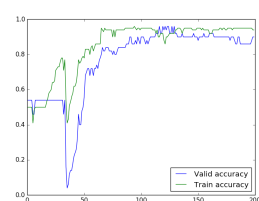
TABLE III shows the KL-divergence between generated fault data and original fault data to evaluate the distribution differences. Comparing these results, the statistical index and KL-divergence of CGAN generated data with Asy_Toeplitz reconstruction are closer to the original fault data.

TABLE III: KL-divergence comparison.

method	Reshape	Sym_Toeplitz	Asy_Toeplitz	Asy_Hankel	Mean
CGAN	0.011	0.014	0.012	0.012	**0.0123**
DCGAN	0.014	0.016	0.013	0.015	0.0145
WGAN	0.017	0.018	0.017	0.017	0.0173



(a) Unbalanced ACC 0.720



(b) Balanced ACC 0.900

Fig. 11: CNN fault detection.

Then CNN method is used to classify the normal and fault operations. The CNN fault detection results are shown in Fig. 11. Here (a) is obtained from an unbalanced dataset (90% original normal data, 10% original fault data), and (b) is an enhanced balanced dataset (50% original normal data, 10% original fault data, 40% fault data are supplied from the generation by CGAN+Asy_Toeplitz method). The figures show that the detection accuracy of enhanced balanced dataset is better than that of the original unbalanced dataset.

V. CONCLUSIONS

This paper addresses the challenge of imbalanced learning in the process industry by generating synthetic fault data to achieve data balance and improve fault diagnosis accuracy. Leveraging the strong learning capabilities of generative adversarial networks (GANs), a novel data conversion framework of "time series data-matrix-image-time series data" is proposed. Four matrix construction methods are compared. The asymmetric Toeplitz method and CGAN demonstrating superior performance. CNN-based fault diagnosis on balanced datasets shows significant improvement over imbalanced datasets, validating the effectiveness of the proposed methods. This study not only resolves the issue of data imbalance but also bridges time series and image domains through deep learning, ultimately enhancing fault classification accuracy in the process industry. These contributions are crucial for advancing fault detection and diagnosis in real-world industrial applications.

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