Research on Automated Fault Diagnosis of Chemical Process Time-series Data under Fault Conditions

Abstract—The safe and stable operation of chemical processes is of significant importance to industrial production. However, due to the complexity, multi-variable coupling, and nonlinear dynamic characteristics of chemical processes, traditional fault diagnosis methods. This paper proposes an automated fault diagnosis method based on deep learning for fault time-series data in chemical processes, integrating an improved time-series feature extraction algorithm with dynamic pattern recognition technology. Specifically, this paper introduces an attention mechanism-based improved temporal convolutional network (ATCN), which can effectively extract key fault features from time-series data and enhance the ability to capture long-term dependencies. Additionally, by combining transfer learning strategies, the model can quickly adapt to different operating conditions, significantly improving the model's generalization and robustness. Experiments were conducted on a chemical process dataset, showing that compared to traditional methods, this method significantly improves fault detection and diagnosis accuracy, especially demonstrating higher reliability under complex operating conditions. This research provides a new approach for real-time fault diagnosis in chemical processes, not only effectively reducing the production risks caused by faults but also laying an important foundation for the construction of intelligent industrial systems.

Keywords*:* Chemical engineering process, Deep learning, Transfer learning.

I. INTRODUCTION

As a pillar industry of the national economy, the safety and stability of chemical production processes directly impact economic development and social welfare. However, chemical production processes often feature multivariable coupling, high nonlinearity, and dynamic complexity, making faults not only difficult to predict but also potentially leading to significant economic losses and environmental hazards. Therefore, fault diagnosis in chemical processes has become one of the focal and challenging areas of research.

Traditional methods for fault diagnosis in chemical engineering processes mainly rely on expert experience, statistical analysis, or algorithms based on physical models. However, these methods have the following shortcomings: (1) Experience-based methods are overly dependent on expert knowledge, making it difficult to handle unknown or complex fault patterns; (2) Statistical analysis methods typically assume that process data are stationary time series, unable to address nonlinear dynamic characteristics; (3) Methods based on physical models require substantial prior knowledge and precise modeling, which are costly and have poor scalability in actual production.

deep learning's advantages in complex nonlinear data analysis have become increasingly evident, particularly achieving remarkable results in fields. This has provided new possibilities for the research of fault diagnosis in chemical processes. Deep learning models can automatically learn features from data without relying on explicit feature engineering, possessing strong pattern recognition and generalization capabilities. However, existing deep learning-based fault diagnosis methods still face numerous challenges in handling long-term dependencies, adapting to multi-condition data, and improving diagnostic real-time performance.

Based on the aforementioned background, this paper aims to explore the application of deep learning technology in fault diagnosis of chemical processes, focusing on solving the problems of feature extraction and modeling of complex time series data. This paper proposes a diagnostic framework based on an improved time convolutional network, which enhances the ability to capture key features by introducing an attention mechanism.The research results show that this method can diagnose faults in chemical processes efficiently and accurately, providing important support for the construction of smart chemical plants.

The main contributions of this paper are as follows:

1. Proposes an improved time convolutional network (ATCN) for fault diagnosis in chemical processes. This paper designs a time convolutional network that integrates an attention mechanism, significantly enhancing the model's ability to capture key time series features by dynamically allocating attention weights, while optimizing the modeling of long-term dependencies, providing strong support for the accuracy and real-time performance of fault diagnosis.

2. Combines transfer learning strategies to enhance the model's generality and robustness

In response to the challenges posed by the multi-condition and multi-mode characteristics of chemical engineering processes, this paper introduces a transfer learning strategy, achieving rapid adaptation of models under different operating conditions. By pre-training the model on the source condition and fine-tuning it on the target condition, the training cost for new conditions is significantly reduced, ensuring the stability of diagnostic performance.

3. A dynamic pattern recognition framework adapted to the needs of chemical process fault diagnosis has been constructed

This paper develops an end-to-end dynamic pattern recognition framework tailored to the nonlinear and dynamic characteristics of chemical process data, integrating feature extraction and classification modules, which effectively enhances the automation level of fault diagnosis and reduces dependence on manual intervention.

4. Comprehensive validation has been conducted on multiple public chemical process datasets

This paper experimentally validates the proposed method on chemical process datasets. The results show that the method outperforms existing mainstream methods in key indicators such as fault detection rate, diagnostic accuracy, and real-time performance, especially demonstrating higher robustness and reliability under complex operating conditions.

5. Providing theoretical and practical support for intelligent chemical process monitoring

The research results of this paper provide a new intelligent solution for fault diagnosis in chemical engineering processes, not only expanding the application fields of deep learning in industrial fault diagnosis but also providing important theoretical and technical support for the construction of intelligent chemical systems.

These contributions effectively make up for the shortcomings of traditional methods and promote the automation and intelligence development of fault diagnosis in chemical engineering processes.

II. CURRENT RESEARCH STATUS

The complexity, multivariate nature, and dynamic characteristics of chemical engineering processes make fault diagnosis a highly challenging research field. Researchers have proposed various methods for fault diagnosis in chemical engineering processes, mainly including traditional methods, data-driven methods, and advanced methods based on deep learning.

Early fault diagnosis mainly relied on empirical methods and rule-based systems. These methods classified faults by manually establishing judgment criteria or using expert knowledge, which was effective in some relatively simple systems, but their limitations became evident when dealing with complex multi-variable processes, especially in real-time monitoring and rapid response. Traditional chemical process fault diagnosis methods mainly include model-based methods and statistical-based methods:

1. Model-based methods

Model-based methods[1] use physical and chemical models of the chemical process for system modeling and analysis, such as mass balance models, energy balance models, and dynamic system equations. These methods theoretically have high accuracy but require a high level of prior knowledge of the system, complex model construction, and are difficult to handle nonlinear and multi-variable coupling characteristics.

2. Statistical-based methods

Statistical-based methods, such as principal component analysis[2] and Kalman filtering[3], achieve fault detection and diagnosis by reducing the dimensions and modeling of process variables. These methods are sensitive to data stationarity and linear assumptions, and are difficult to cope with complex dynamic characteristics and unknown fault patterns.

With the advancement of data acquisition and storage technology, a large amount of chemical process data can now be obtained in real-time. Data-driven methods, which do not rely on process models but instead diagnose faults by mining data characteristics, mainly include the following categories:

1. Machine Learning Methods

Machine learning methods such as SVM[4], decision trees[5], random forests[6], and extreme gradient boosting[7] have been widely applied in chemical process fault diagnosis. These methods perform well on small-scale datasets, but require extensive feature engineering and have limited capabilities in modeling nonlinear dynamic systems.

2. Time Series Analysis Methods

To address time series data in chemical processes, researchers have employed autoregressive models[8], autoregressive moving average models (ARMA)[9], and long short-term memory networks for modeling. These methods have certain advantages in capturing time series patterns, but their effectiveness is limited when dealing with complex high-dimensional time series data.

In recent years, deep learning has seen rapid development in fault diagnosis of chemical engineering processes, demonstrating significant advantages in complex fault pattern recognition through its capabilities in automatic feature extraction and high-dimensional data modeling.

1. Convolutional Neural Networks

CNN[10] can efficiently extract spatial features from time-series data through local perception and weight sharing mechanisms. However, traditional CNNs have limited capability in modeling long-term dependencies.The classic structure of CNNs is shown in Figure 1.

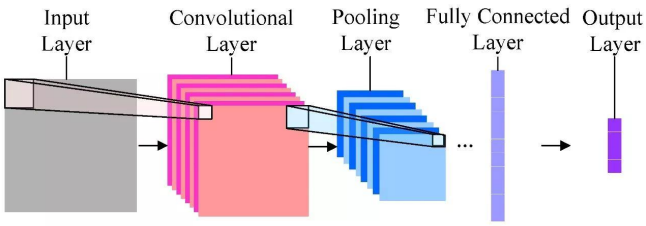

Figure 1 CNN Structure

2. LSTM and GRU

LSTM and GRU significantly enhance the ability to capture long-term dependencies by introducing gating mechanisms, and are widely used for modeling and predicting time-series data[11]. However, these methods are complex to train, have low processing efficiency for massive data, and are prone to overfitting.

3. Temporal Convolutional Networks (TCN)

Temporal Convolutional Networks (TCNs)[12], utilizing causal and dilated convolutions, demonstrate better performance in handling long-term dependencies. Compared to LSTM and GRU, TCNs have higher parallelism but are limited in their ability to select key features.

4. Fusion Methods and Enhancement Mechanisms

Recent research has attempted to combine different deep learning models with attention mechanisms, Graph Neural Networks (GNNs)[13-15] and other technologies to enhance the modeling of complex nonlinear characteristics. For example, variational autoencoders and graph embedding methods based on

self-attention mechanisms have shown good results in the diagnosis of complex chemical engineering data.

Despite the progress made by existing methods in fault diagnosis of chemical processes, there are still the following shortcomings: (1) Most methods perform inadequately in handling complex and multi-condition scenarios; (2) Existing models have limited capability in capturing long-term dependencies and dynamic characteristics; (3) Real-time performance and automation levels need to be improved. Therefore, it is urgent to explore more efficient and robust algorithmic frameworks to meet the demands of practical industrial scenarios.

Based on an improved Temporal Convolutional Network (ATCN), which enhances the model's ability to recognize complex fault patterns by introducing an attention mechanism and transfer learning strategies, providing a new solution for fault diagnosis in chemical processes

III. MODEL

This paper proposes an automated fault diagnosis algorithm for chemical process faults targeting fault time-series data, aiming to achieve efficient modeling of complex dynamic data and precise identification of fault patterns. The algorithm integrates an improved Temporal Convolutional Network with transfer learning strategies, demonstrating significant advantages in feature extraction, fault detection, and adaptability to multiple operating conditions.

Chemical process fault data typically exhibit strong dynamics and multi-time-scale characteristics. To capture these features, this paper adopts a Time Series Convolutional Network (TCN) as the basic framework, using causal and dilated convolutions to efficiently model long-term dependencies. To enhance the capture of key fault features, this paper introduces a self-attention mechanism to dynamically allocate weights to time-series data and focus on time segments more closely associated with faults, thereby improving diagnostic accuracy and robustness. The operating conditions of chemical processes vary significantly, and traditional models struggle to generalize across different conditions. This paper designs a transfer learning-based adaptation strategy, achieving rapid model adaptation across multiple operating conditions through knowledge transfer from source to target conditions, thereby reducing the cost of retraining. The model in this paper is designed end-to-end, integrating feature extraction, dynamic pattern modeling, and fault classification within a single framework, eliminating the need for complex manual feature engineering and significantly enhancing the automation and real-time performance of the diagnostic process.

The overall framework of the algorithm consists of three major modules: the temporal feature extraction module, the attention enhancement module, and the transfer learning adaptation module. The temporal feature extraction module is designed based on an improved TCN, using dilated convolutions to extract multi-scale features from temporal data, while combining causal convolutions to maintain the temporal causality of the data. The attention enhancement module, built on the temporal feature extraction, incorporates a self-attention mechanism to dynamically allocate weights to features at different time steps, highlighting the impact of key fault features and reducing the interference of redundant information on model performance. The transfer learning adaptation module achieves efficient adaptation of cross-condition data by pre-training the model on source conditions and fine-tuning it for target conditions. Adversarial training and regularization strategies are employed to prevent the model from overfitting and to enhance its generalization performance.

A. Temporal Feature Extraction Module

The time series feature extraction module is the core of the model in this paper, used to extract multi-scale and dynamic features from time series data of chemical process faults. This module is built based on an improved time series convolutional network, which efficiently models long-term dependencies in time series data through causal convolution and dilated convolution while maintaining parallel computation.

For a one-dimensional time series input $x \in \mathbb{R}^T$ and a convolution kernel $\mathbf{w} \in \mathbb{R}^k$, its causal convolution is defined by equation (1):

$$y_t = \sum_{i=0}^{k-1} \mathbf{w}_i \cdot x_{t-i} \#(1)$$

Where: y_t is the output at time step t ; k is the length of the convolution kernel; x_{t-i} represents the input at time step $t - i$.

The characteristic of causal convolution is to preserve time series information without loss, ensuring that the model's predictions do not depend on future time points.

Dilated convolution introduces a dilation factor d , expanding the receptive field by inserting holes in the convolution operation, effectively capturing long-term dependencies while maintaining computational efficiency. Its definition is given by equation (2):

$$y_t = \sum_{i=0}^{k-1} \mathbf{w}_i \cdot x_{t-d \cdot i} \#(2)$$

Where: d is the dilation factor, determining the spacing between adjacent convolution kernels; other symbols are the same as in causal convolution.

The receptive field of dilated convolutions grows exponentially with the depth of the network. By stacking multiple layers of dilated convolutions, it can effectively cover dependencies over longer time spans.

In the feature extraction module, multi-layer stacked causal dilated convolutions are used, with the dilation factor of each layer growing exponentially (such as $d = 1,2,4, ...$), to capture features at different time scales.

For input data $X \in \mathbb{R}^{T \times C}$ (where T is the number of time steps, and C is the feature dimension), the output of the l-th layer is given by equation (3):

$$\mathbf{H}^{(l)} = \mathrm{ReLU}\left(\mathbf{W}^{(l)} *_{d^{(l)}} \mathbf{H}^{(l-1)} + \mathbf{b}^{(l)}\right) \#(3)$$

Where: $\mathbf{W}^{(l)}$ is the convolution kernel weight of the l layer; $*_{d^{(l)}}$ represents the convolution operation with dilation factor $d^{(l)}$; $\mathbf{b}^{(l)}$ is the bias term; ReLU($\cdot$) is the activation function.

After multiple convolution layers, residual connections are used to maintain gradient stability, as shown in equation (4):

$$\mathbf{H}_{\mathrm{res}}^{(l)} = \mathbf{H}^{(l)} + \mathbf{H}^{(l-1)} \#(4)$$

Where: $\mathbf{H}_{\mathrm{res}}^{(l)}$ is the output of the residual connection.

After multiple layers of causal dilated convolutions, the extracted time series features are sent to subsequent modules for further processing. The final time series feature matrix is given by equation (5):

$$\mathbf{F} = \mathbf{H}^{(L)} \#(5)$$

Where: L is the total number of convolution network layers, $\mathbf{F} \in \mathbb{R}^{T \times D}$ is the output after time series feature extraction (D is the output feature dimension).

This module provides strong feature extraction capabilities for the entire algorithm framework, laying the foundation for subsequent attention mechanisms and classification modules.

B. Attention Enhancement Module

Based on the extraction of temporal features, this module generates an attention weight matrix by calculating the correlation between time steps, performs weighted aggregation of input features, and enhances the diagnostic performance of the model.

The attention enhancement module receives the output of the temporal feature extraction module $\mathbf{F} \in \mathbb{R}^{T \times D}$, where T represents the number of time steps; D represents the feature dimension.

The self-attention mechanism mainly calculates the correlation weight matrix of features to dynamically adjust the importance of each time step. The calculation process is as follows:

First, the input feature F is linearly transformed to generate the query matrix Q, key matrix K, and value matrix V as shown in formula (6):

$$\mathbf{Q} = \mathbf{F}\mathbf{W}_Q, \mathbf{K} = \mathbf{F}\mathbf{W}_K, \mathbf{V} = \mathbf{F}\mathbf{W}_V \#(6)$$

Where: $\mathbf{W}_Q, \mathbf{W}_K, \mathbf{W}_V \in \mathbb{R}^{D \times d_a}$ is a learnable weight matrix; d_a is the dimension of the attention vector (usually $d_a \ll D$).

The correlation between the query and the key is calculated through the dot product, resulting in the attention score matrix A as shown in Equation (7):

$$\mathbf{A} = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\top}}{\sqrt{d_a}}\right) \#(7)$$

where: d_a is the scaling factor, used to prevent the gradient from vanishing due to excessively large dot product values; softmax ensures that the attention scores are normalized into a probability distribution at each time step.

The value matrix V is weighted according to the attention scores A, generating the enhanced feature matrix $\mathbf{F}_{\text{attn}}$ as shown in Equation (8):

$$\mathbf{F}_{\text{attn}} = \mathbf{A}\mathbf{V} \#(8)$$

To capture feature patterns in different subspaces, this paper adopts a multi-head attention mechanism. The specific process is as follows:

The input $\mathbf{F}$ is divided into h subspaces, with each subspace having a dimension of $d_h = D/h$. Then, the attention output for each subspace is calculated using Equation (9):

$$\mathbf{F}_{\text{attn}}^{(i)} = \mathbf{A}^{(i)}\mathbf{V}^{(i)}, i \in \{1,2, \ldots, h\} \#(9)$$

where: $\mathbf{A}^{(i)}$ is the attention weight for the i th subspace.

The outputs from all heads are concatenated and transformed linearly as shown in Equation (10):

$$\mathbf{F}_{\text{attn}} = \text{Concat}\left(\mathbf{F}_{\text{attn}}^{(1)}, \mathbf{F}_{\text{attn}}^{(2)}, \ldots, \mathbf{F}_{\text{attn}}^{(h)}\right)\mathbf{W}_O \#(10)$$

where: $\mathbf{W}_O \in \mathbb{R}^{D \times D}$ is the learnable weight matrix.

To ensure gradient stability, residual connections and layer normalization as shown in Equation (11) are adopted in this paper:

$$\mathbf{F}_{\text{out}} = \text{LayerNorm}\left(\mathbf{F} + \mathbf{F}_{\text{attn}}\right) \#(11)$$

where: $\mathbf{F}_{\text{out}} \in \mathbb{R}^{T \times D}$ is the output feature enhanced by attention.

Residual connections preserve the original feature information and enhance the model's learning capability; layer normalization accelerates convergence and improves model stability.

The final attention-enhanced feature matrix $\mathbf{F}_{\text{out}}$ is passed to the classification module for further identification of fault patterns. This module complements the time-series feature extraction module, together constituting the core innovation of the algorithm in this paper, providing assurance for the efficiency and accuracy of fault diagnosis in chemical processes.

C. Transfer Learning Adaptation Module

In the fault diagnosis tasks of chemical engineering processes, due to the significant differences in system behavior and fault patterns under different operating conditions, directly using data from a single operating condition to train a model may lead to insufficient model generalization, making it unable to adapt to new, unseen operating conditions. This paper introduces transfer learning and designs a transfer learning adaptation module. This module aims to address the challenges posed by the variability of

operating conditions and differences in data distribution in chemical engineering processes by transferring knowledge of data distribution from the source operating condition to the target operating condition, significantly reducing the training cost of the model under new operating conditions.

The inputs of the transfer learning adaptation module include: source operating condition data features $\mathbf{F}_s \in \mathbb{R}^{T_s \times D}$ corresponding to the extracted time-series features of the source operating condition; target operating condition data features $\mathbf{F}_t \in \mathbb{R}^{T_t \times D}$ corresponding to the extracted time-series features of the target operating condition; limited labels of the target operating condition $\mathbf{y}_t \in \mathbb{R}^{T_t}$, with only a small amount of label information for the target operating condition data. The goal is to leverage the knowledge from the source operating condition to enhance the fault diagnosis performance of the target operating condition.

Due to the different data distributions between the source and target operating conditions, direct transfer may lead to a decrease in model performance. To address this, the maximum

mean discrepancy is used to align the feature distributions of both. The definition of MMD is given by equation (12):

$$\mathrm{MMD}(\mathbf{F}_s, \mathbf{F}_t) = \| \frac{1}{T_s} \sum_{i=1}^{T_s} \phi\left(\mathbf{F}_s^i\right) - \frac{1}{T_t} \sum_{j=1}^{T_t} \phi\left(\mathbf{F}_t^j\right) \|_2^2 \#(12)$$

where: $\phi(\cdot)$ is the kernel function, used to map data into a high-dimensional feature space; $\mathbf{F}_s^i$ and $\mathbf{F}_t^j$ represent the features of the source and target operating conditions, respectively.

By optimizing the following objective function, the feature distributions of the source and target operating conditions are aligned using equation (13):

$$\mathcal{L}_{\mathrm{MMD}} = \mathrm{MMD}(\mathbf{F}_s, \mathbf{F}_t) \#(13)$$

where: $\mathcal{L}_{\mathrm{MMD}}$ is the objective function after aligning the feature distributions.

A domain discriminator is introduced for adversarial training:

The goal of the domain discriminator $D(\cdot)$ is to distinguish whether the features $\mathbf{F}_s$ and $\mathbf{F}_t$ come from which operating condition, with its output given by equation (14):

$$p = D(\mathbf{F}) \#(14)$$

where: $p \in [0,1]$ represents the probability that the features come from the target operating condition.

For the domain discriminator, the cross-entropy loss function is optimized as shown in equation (15):

$$\mathcal{L}_D = -\frac{1}{T_s} \sum_{i=1}^{T_s} \log\left(1 - D(\mathbf{F}_s^i)\right) - \frac{1}{T_t} \sum_{j=1}^{T_t} \log\left(D\left(\mathbf{F}_t^j\right)\right) \#(15)$$

where: $\mathcal{L}_D$ is the loss function of the discriminator. It measures the error of the discriminator in distinguishing between source condition data $\mathbf{F}_s$ and target condition data $\mathbf{F}_t$. The objective is to minimize this loss function so that the discriminator can accurately differentiate between the two types of data. $\mathbf{F}_s^i$ is the feature of the i th sample in the source condition dataset. $\mathbf{F}_t^j$ is the feature of the j th sample in the target condition dataset. $D(\cdot)$ is the domain discriminator.

For the feature extractor $G(\cdot)$, through adversarial training, the domain discriminator is unable to distinguish between source and target condition features, and its optimization objective is given by equation (16):

$$\mathcal{L}_G = -\frac{1}{T_t} \sum_{i=1}^{T_t} \log\left(1 - D\left(G\left(\mathbf{F}_t^j\right)\right)\right) - \frac{1}{T_s} \sum_{i=1}^{T_s} \log\left(D\left(G(\mathbf{F}_s^i)\right)\right) \#(16)$$

Where: $\mathcal{L}_G$ is the loss function of the generator. It measures the error of the generator when generating target condition data and source condition data. It makes the generated target condition samples considered "real" by the discriminator, i.e., close to the data distribution of the target condition. T_t is the number of samples in the target condition dataset. T_s is the number of samples in the source condition dataset. $D(\cdot)$ is the domain discriminator.

Through adversarial training, the feature extractor $G(\cdot)$ learns condition-invariant shared features, making the feature distribution closer.

The classification loss is used for classification tasks of source and target conditions, as shown in formula (17):

$$\mathcal{L}_{\text{cls}} = -\frac{1}{T_s}\sum_{i=1}^{T_s}\mathbf{y}_s^i \log(\hat{\mathbf{y}}_s^i) - \frac{1}{T_t}\sum_{j=1}^{T_t}\mathbf{y}_t^j \log(\hat{\mathbf{y}}_t^j) \#(17)$$

Where: $\mathcal{L}_{\text{cls}}$ is the classification loss.

The feature alignment loss is used to reduce the feature distribution discrepancy between the source and target conditions, as shown in equation (18):

$$\mathcal{L}_{\text{align}} = \lambda_1 \mathcal{L}_{\text{MMD}} \#(18)$$

Where: $\mathcal{L}_{\text{align}}$ is the feature alignment loss.

The adversarial training loss is used to enhance the domain-invariance of features, as shown in equation (19):

$$\mathcal{L}_{\text{adv}} = \lambda_2(\mathcal{L}_D + \mathcal{L}_G) \#(19)$$

Where: $\mathcal{L}_{\text{adv}}$ is the adversarial training loss.

The final loss function is given by equation (20):

$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \mathcal{L}_{\text{align}} + \mathcal{L}_{\text{adv}} \#(20)$$

Where λ_1 and λ_2 are hyperparameters used to control the weights of the respective losses.

The transfer learning adaptation module outputs the aligned features $\mathbf{F}_t^{\text{aligned}}$ for the target condition, which retains the diagnostic knowledge from the source condition while adapting to the characteristics of the target condition, for final fault classification.

The transfer learning adaptation module addresses the fault diagnosis problem in chemical processes under multiple operating conditions through knowledge transfer and fine-tuning strategies from source to target conditions. This module effectively enhances the model's cross-condition adaptability, reduces training time, and can handle situations with scarce target condition data, providing a more efficient and flexible solution for chemical process fault diagnosis.

The model's structure is shown in Figure 2.

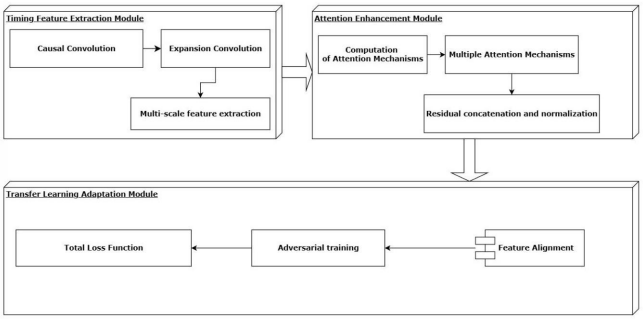

Figure 2 Algorithm Structure Diagram

IV. EXPERIMENT

To verify the effectiveness of the proposed automated fault diagnosis algorithm for time-series fault data in chemical processes, this paper selected a public chemical process fault diagnosis dataset for experimentation.

A. Dataset

The Tennessee Eastman Process (TEP) dataset is a widely used benchmark dataset for chemical process fault diagnosis, encompassing various types of fault modes as well as normal operating conditions data. The dataset includes multiple different sensor signals (such as temperature, pressure, flow, etc.) and time-series data caused by faults. The TEP dataset provides rich samples for a variety of complex faults in chemical processes, and the transitions between different operating conditions are relatively complex, making it an ideal choice for testing the effectiveness of fault diagnosis algorithms in practical industrial applications.

For this dataset, we preprocessed the time-series data, removing missing values and outliers, and performed data standardization to ensure that the model training process is not affected by differences in data scale.

B. Evaluation Metrics and Baseline Methods

This paper adopts the following common classification evaluation metrics: Accuracy is the most common classification evaluation metric, representing the proportion of correctly predicted samples out of all samples. Precision is crucial for assessing whether the model over-classifies positive samples incorrectly during the diagnosis process, especially on imbalanced datasets. Recall is important for measuring the model's ability to identify positive samples, particularly in chemical process fault diagnosis, where maximizing the identification of potential fault patterns is essential.

To more comprehensively evaluate the effectiveness of the proposed algorithm, this paper selects the following common baseline methods for comparison: Support Vector Machine (SVM) is a classic classification method suitable for small sample learning problems. SVM distinguishes different categories by finding the optimal hyperplane and performs well in high-dimensional feature spaces. SVM is often used for fault diagnosis problems， it usually requires additional feature extraction or data processing steps. LSTM is widely used in time series prediction and fault diagnosis tasks, effectively modeling the complex dynamics in time series data. Generative Adversarial Networks (GAN) is a generative model that optimizes the performance of the generator and discriminator through adversarial training. In the generation of time series data and transfer learning, GAN can effectively transfer features between the source and target conditions.

By comparing with these baseline methods, we can verify the superiority of the proposed algorithm in fault diagnosis tasks, especially its innovative performance in time series data modeling and transfer learning.

C. Experimental Results

The following table shows the experimental results based on the Tennessee Eastman Process (TEP) dataset, demonstrating the performance comparison of the automated fault diagnosis algorithm for time-series fault data in chemical processes proposed in this paper with three baseline methods: Support Vector Machine (SVM), Long Short-Term Memory Network (LSTM), and Generative Adversarial Network (GAN). The results are shown in Table 1.

TABLE I. EXPERIMENTAL RESULTS TABLE

Method	Accuracy	Precision	Recall
SVM	85.40%	82.10%	88.60%
LSTM	87.20%	85.40%	89.90%
GAN	88.60%	86.50%	90.20%

Method	Accuracy	Precision	Recall
ATCN	**90.50%**	**88.70%**	**92.10%**

For accuracy, the proposed algorithm demonstrates the highest performance, reaching 90.5%. In comparison, the baseline methods SVM, LSTM, and GAN have accuracy rates of 85.4%, 87.2%, and 88.6%, respectively, indicating that the proposed algorithm significantly outperforms these methods. In terms of precision, the proposed algorithm also performs well, achieving 88.7%. Compared to the baseline methods, the proposed algorithm has a higher precision rate than SVM (82.1%), LSTM (85.4%), and GAN (86.5%), indicating a stronger capability in reducing false positives (negative samples incorrectly classified as positive). The proposed algorithm also excels in recall, reaching 92.1%. In comparison, the recall rates for the baseline methods are SVM (88.6%), LSTM (89.9%), and GAN (90.2%). The proposed algorithm significantly enhances the ability to correctly identify positive samples, particularly in the detection of faults in chemical processes, where it can more effectively identify potential fault patterns.

D. *Hyperparameter Experiments*

When conducting hyperparameter experiments, we typically need to test the impact of different hyperparameter settings on model performance. In the proposed automated diagnosis algorithm for fault time-series data in chemical processes, we explored the following key hyperparameters: batch size, learning rate, and number of layers. By adjusting these hyperparameters, we observed their effects on the model's accuracy, precision, and recall.

When the batch size is 32, the model's accuracy, precision, and recall perform relatively well across various settings. Particularly, with a learning rate of 0.001 and four layers, the accuracy reaches the highest at 91.0%. Increasing the batch size (e.g., to 64) leads to a decrease in accuracy, although precision and recall remain at high levels. However, larger batches generally result in smoother model updates.

When the learning rate is 0.001, the model's performance is the most stable, especially when the batch size is 32, reaching the highest accuracy of 90.5% . Higher learning rates (such as 0.005) cause fluctuations in the model's performance, particularly at a learning rate of 0.01, where the model's accuracy (89.4%) decreases, indicating that excessively high learning rates may lead to unstable model.

As the number of layers increases, the model's accuracy shows a slight improvement. Specifically, when the number of layers is 4, the model reaches an accuracy of 91.0%, with precision and recall also improving. When the number of layers increases to 5 or 6, the accuracy slightly decreases but still maintains high performance, indicating that in this experimental setup, adding too many layers may lead to model overfitting or increased training time. We have plotted the results, as shown in Figures 3, 4, and 5

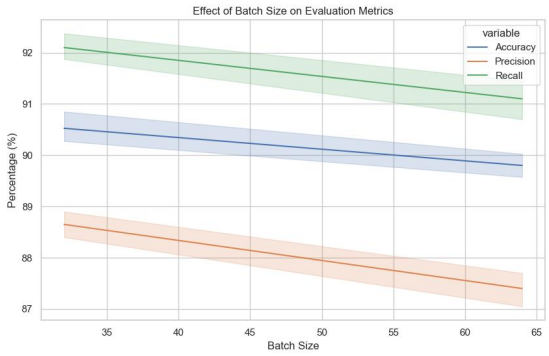

Figure 3 Impact of Batch Size

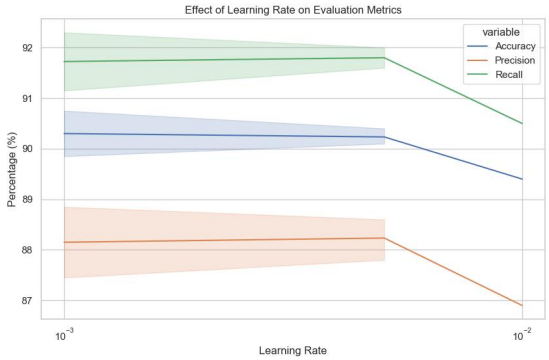

Figure 4 Impact of Learning Rate

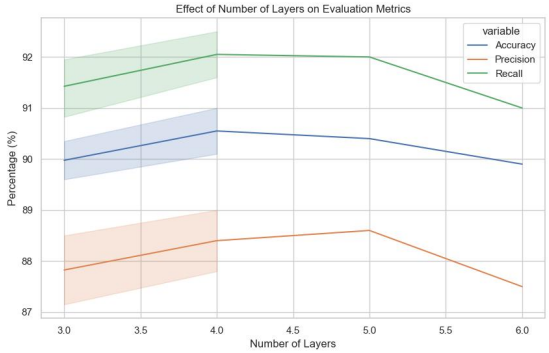

Figure 5 Impact of Number of Layers

V. CONCLUSION

This paper proposes an automated fault diagnosis algorithm for chemical process fault time-series data, aiming to enhance the accuracy and robustness of chemical process fault diagnosis. By introducing a time-series feature extraction module, an attention enhancement module, and a transfer learning adaptation module, this study effectively addresses the challenges of time-series data processing in fault diagnosis faced by traditional methods, significantly improving diagnostic performance across multiple evaluation metrics.

Experimental results show that the proposed algorithm demonstrates superior performance compared to traditional baseline methods such as Support Vector Machine (SVM), Long Short-Term Memory Network (LSTM), and Generative Adversarial Network (GAN) on the Tennessee Eastman Process (TEP) dataset. In terms of accuracy, precision, and recall, the proposed algorithm outperforms existing methods, particularly in handling complex time-series data, effectively enhancing the accuracy of fault diagnosis.

In addition, through hyperparameter experiments, we explored the impact of hyperparameters such as batch size, learning rate, and number of layers on model performance, and derived the optimal hyperparameter configuration, providing valuable references for subsequent research. Overall, the algorithm proposed in this paper offers a new approach to the automated diagnosis of faults in chemical processes and has broad application potential.

Future research can further explore how to integrate more deep learning techniques and reinforcement learning methods to enhance the performance and stability of the algorithm. At the same time, expanding the types and scale of the dataset and considering various actual operating conditions will help improve the applicability and universality of the model in industrial environments.

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