IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Traitement du Signal
Vol. 42, No. 1, February, 2025, pp. 423-431
Journal homepage: http://iieta.org/journals/ts

Conditional Generative Adversarial Network Based on Self-Attention Mechanism and VAE Algorithm and Its Applications

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https://doi.org/10.18280/ts.420136

Received: 8 June 2024
Revised: 19 October 2024
Accepted: 3 December 2024
Available online: 28 February 2025

Keywords:
Conditional Generative Adversarial Network (cGAN), Variational Autoencoder (VAE), self-attention mechanism (SAM), long-range dependencies, projection encoding algorithm

ABSTRACT

Generative Adversarial Networks (GANs) still face issues such as a lack of diversity in generated samples, incomplete encoding techniques, and a simplistic evaluation system. Based on this, the paper proposes a "Conditional Generative Adversarial Network based on self-attention mechanism and Variational Autoencoder (VAE) Algorithm and Its Applications." The proposed algorithm consists of three sub-algorithms. The Variational Autoencoder (VAE) algorithm based on a self-attention mechanism adaptively constructs a latent space based on training data, thereby enhancing the diversity of generated samples. The A self-adaptive encoding method integrating self-attention and conditional vector projection. This method combines the self-attention mechanism and projection encoding algorithm to capture long-range dependencies in the data, addressing the issue of incomplete encoding techniques. Multi-metric Weighted Evaluation Algorithm is developed, which comprehensively evaluates the quality and diversity of generated samples, the conditional dependencies of the model, and the similarity between the distributions of input and generated samples. The evaluation metrics can be controlled adaptively through weight λ_i.The study constructs a financial dataset of higher education institutions containing 1,200 records and trains the proposed conditional GAN on this dataset. The network is then used to generate synthetic data for the detection of counterfeit data. Experimental results demonstrate that the proposed algorithm is feasible, stable, and shows comparative advantages.

1. INTRODUCTION

The financial security risk detection model based on intelligent big data analysis technology can significantly improve the accuracy and reliability of financial security risk detection, quickly identify abnormal financial data, and prevent potential security risks. Therefore, AI-based intelligent analysis and identification methods for financial data are an important guarantee for financial data security. Among them, the use of Generative Adversarial Networks [1] (GANs) in financial data analysis and identification holds significant theoretical and practical value. With the rapid advancement of research in Generative Adversarial Networks (GANs) theory and applications, GANs have provided effective theories and methods for signal, text, and image data analysis and identification. Innovative research primarily focuses on new network architectures, loss functions, and training strategies.

1.1 Network architecture and training process reconstruction

Common algorithms include: Deep Convolutional GAN (DCGAN) [2], which solves the training stability issue by imposing constraints on the architectural topology; to address the issue of insufficient labeled data in adversarial neural networks, this algorithm [3] integrates Coevolutionary Algorithms with Semi-Supervised GANs (SSL-GANs). By leveraging a hybrid training approach that combines limited labeled data with unlabeled data, we achieve a high-performance classifier and high-quality image generator. This strategy stacks multiple generators and discriminators, using aggregation operators to coordinate the outputs of the multiple generators, thereby improving the quality and complexity of the generated samples to produce finer and more realistic data or images. Typical examples include Stacked GANs [4, 5], Ensembles of GANs [6, 7], and AdaGANs [8].

1.2 Loss function reconstruction

When the discriminator of the original GAN reaches its optimum, the generator's loss function has a certain relationship with the JS divergence. Therefore, to address the issues related to training instability, the original loss function is reconstructed (the lower bound of Jensen-Shannon divergence). Typical algorithms include: The gradient penalty-based Wasserstein-1 distance [9, 10] loss function, which effectively solves problems such as vanishing gradients and mode collapse during GAN training; A loss function based on quantile regression techniques is proposed to implicitly drive the generator to learn the inverse of the cumulative distribution function, addressing the issue of variable conditional distribution [11]; A loss function based on the chi-square distance is reconstructed to effectively measure the difference between two probability distributions [12]. A discriminator and loss function based on the energy function are proposed to map low energy values to high data density regions, enabling the generator to focus on low-energy regions during sampling [13].

The aforementioned literature explores innovations in network architecture, loss functions, and training methods in Generative Adversarial Networks (GANs), achieving significant theoretical and practical results. However, in data signal processing, Generative Adversarial Networks (GANs) still have the following shortcomings. (1) The problem of generating monotonous samples; (2) The issue of imperfect coding techniques; (3) The problem of a simplistic evaluation system. Based on this, this paper proposes "Conditional Generative Adversarial Network (cGAN) Based on self-attention mechanism and VAE Algorithm and Its Applications." The innovations of this method include the following main aspects.

(1) Rich generated samples

The Variational Autoencoder (VAE) [14] algorithm based on a self-attention mechanism adaptively constructs a latent space based on training data, thereby enhancing the diversity of generated samples.

(2) Advanced coding techniques

A self-adaptive distribution learning method that integrates self-attention and condition vector projection. This method combines the self-attention mechanism [15] and projection encoding algorithm [16] to capture long-range dependencies in the data, addressing the issue of incomplete encoding techniques.

(3) Evaluation system based on multi-criteria fusion. A weighted evaluation metric is developed, which comprehensively evaluates the quality and diversity of generated samples, the conditional dependencies of the model, and the similarity between the distributions of input and generated samples. The evaluation metrics can be controlled adaptively through weight λ_i.

(4) The financial dataset of higher education. The study constructs a financial dataset of higher education institutions containing 7,236 records and trains the proposed conditional GAN on this dataset.

Based on the aforementioned innovations, this paper will effectively address the problems of generating monotonous samples, imperfect coding techniques, and a simplistic evaluation system.

2. RELATED WORK

2.1 The current state of research on financial data based on GANs

Financial/financial data is a type of data signal with strong data attributes. research on financial/financial data generation and identification based on GANs is emerging, Innovations primarily focused on the application of GANs in this domain to address data generation, data identification, and data-assisted decision-making challenges. The main research areas include:

Takahashi et al. [17] proposed "Modeling financial time-series with Generative Adversarial Networks" to address the statistical mechanisms underlying financial time series modeling. This method leverages Generative Adversarial Networks (GANs) to learn the data characteristics and generate realistic data in a data-driven manner. The time series generated by the GAN model can restore the statistical properties of financial time series. Experimental results confirm the feasibility of this approach. To address the issue of financial fraud detection, represented by credit card fraud, Zhao et al. [18] proposed a self-attention-based Generative Adversarial Network model (SAGANs) in "Advancing financial fraud detection: Self-attention Generative Adversarial Networks for precise and effective identification." To optimize and improve fraud detection algorithms, the model extracts key features and patterns from large-scale transaction datasets, deepening the mathematical abstraction of credit card fraud data and enhancing the accuracy of identification. To address the issue of systematic trading strategy optimization, Koshiyama et al. [19] proposed "Generative Adversarial Networks for financial trading strategies fine-tuning and combination" and developed a complete methodology based on training and selection of cGAN, single-sample strategy calibration, and multi-sample generative modeling. Experiments show that the algorithm provides a feasible and effective approach to solving the problem of systematic trading strategy optimization. In "DeepPricing: pricing convertible bonds based on financial time-series Generative Adversarial Networks," Tan et al. [20] proposed a novel data-driven convertible bond pricing model, DeepPricing, which effectively addresses the pricing problem of convertible bonds. The algorithm introduces a new type of financial time-series Generative Adversarial Network (FinGAN) to generate risk-neutral stock return processes that preserve the original statistical properties. This allows the model to capture the dynamic changes of the underlying stock return process while retaining the rich characteristics of the convertible bond market. Experimental results show that the proposed algorithm outperforms traditional methods in convertible bond pricing. Lin et al. [21] proposed an efficient credit default swap (CDS) prediction model based on Generative Adversarial Networks in "Credit default swap prediction based on Generative Adversarial Networks" to enhance the intelligence of credit risk management and provide investors with more accurate risk management and trading strategy support. In their paper Fin-GAN: Forecasting and Classifying Financial Time Series via Generative Adversarial Networks, Vuletić et al. [22] proposed a specialized adversarial neural network with an improved loss function to explore the application of Generative Adversarial Networks (GANs) in financial time series probabilistic forecasting. This network effectively solves the challenges associated with applying GANs in this context. Experimental results demonstrate that the model surpasses traditional supervised learning models in terms of the Sharpe ratio. To explore the similarity between synthetic data sequences generated by Wasserstein GAN and real data sequences, Allen et al. [23] employed various metrics, including regression analysis, the application of moments and characteristic functions, and random forest analysis, in their paper *GANs and Synthetic Financial Data: Calculating VaR*. They also evaluated and applied the data by calculating the Value at Risk (VaR). To solve the problems of insufficient prior knowledge and high time complexity in urban master plan rendering, in response to the challenges of employing stochastic processes in financial time series modeling, Wiese et al. [24] introduced a data-driven Quant GANs model in their paper "Quant GANs: Deep Generation of Financial Time Series". The model's generator ensures that the generated stochastic processes transition effectively to their risk-neutral distribution. Numerical experiments indicate that the distribution characteristics of the generated data closely align with those of real data. In exploring the applicability of deep generative models in the financial domain, Park et al. [25] propose a stock feature-based deep generative diffusion model in their paper *Modeling Asset Price Process: An Approach for Imaging Price Chart with Generative Diffusion Models*. This model effectively avoids prior assumptions about stock price movements, enabling a more accurate representation and generation of financial data. Experimental results demonstrate that the algorithm can successfully replicate well-known asset price processes, providing a novel approach for financial decision-making. Reinforcement learning models used in portfolio management have certain drawbacks, leading to suboptimal generalization results. In this regard, Kuo et al. [26] introduced an interactive generative adversarial model based on a limit order book to simulate financial markets in their paper *Improving Generalization in Reinforcement Learning-Based Trading by Using a Generative Adversarial Market Model*. The experimental results demonstrate that the framework improves out-of-sample portfolio performance by 4%, outperforming other generalization techniques.

2.2 Basis of Method Innovation

2.2.1 Generative Adversarial Networks

Generative Adversarial Networks (GANs) are a deep learning model consisting of a generator $G(z,\Theta_G)$ and a discriminator $D(x^*,\Theta_D)$, which follow the principles of zero-sum game theory, optimization theory, and Nash equilibrium. The generator $G(z,\Theta_G)$ is a neural network that generates synthetic samples $\bar{x}$ from noise z based on a prior distribution $p_z(z)$, aiming to make $\bar{x}$ as similar as possible to real data samples xx. The discriminator $D(x^*,\Theta_D)$ is a neural network designed to distinguish whether an input sample x^* originates from the real data distribution xx or is a synthetic sample $\bar{x}$ generated by the generator. Here, Θ_G and Θ_D represent the parameters of the generator and discriminator, respectively. The value function is denoted as $V(G,D)$. Therefore, the Generative Adversarial Network can be formulated as follows:

$$G(z,\Theta_G) : \mathrm{z} \rightarrow \bar{\mathrm{x}} \tag{1}$$

$$D(x^*,\Theta_D) : x^* \rightarrow [0,1] \tag{2}$$

$$\begin{aligned}\min_G \max_D V(D,G) = E_{X\sim P_{data(x)}}[\log D(x)] \\ + E_{z\sim P_{z(z)}}\left[log\left(1-D\big(G(z)\big)\right)\right]\end{aligned} \tag{3}$$

Eqs. (1)-(3) describe the Generative Adversarial Network (GAN) model and outline the improvement paths for the network.

2.2.2 Conditional Generative Adversarial Network

Conditional Generative Adversarial Network (cGAN) is a variant of Generative Adversarial Networks (GAN) that incorporates implicit conditions. By introducing a condition c into both the generator $G(z|c,\Theta_G)$ and the discriminator $D(x^*|c,\Theta_D)$, cGAN achieves two key improvements: (1) The generator $G(z|c,\Theta_G)$ produces samples $\bar{x}$ that not only retain stochastic properties but also incorporate conditional attributes, enabling the generation of samples with specified features based on given conditions; (2) The discriminator $D(x^*|c,\Theta_D)$ performs authenticity verification of the sample x^* based on the condition c, allowing for condition-dependent discrimination. The cGAN framework is described as follows:

$$G(z|c,\Theta_G): z, c \rightarrow \bar{x} \tag{4}$$

$$D(x^*|c,\Theta_D): x^*, c \rightarrow [0,1] \tag{5}$$

$$\begin{aligned}\min_G \max_D V(D,G) = E_{X\sim P_{data(x)}}[\log D(x\,|c)] \\ + E_{z\sim P_{z(z)}}\left[log\left(1-D\big(G(z|c)\big)\right)\right]\end{aligned} \tag{6}$$

$E_{X\sim P_{data(x)}}[\log D(x\,|c)]$ represents the discriminator's loss on real samples, indicating its ability to determine whether a real sample x belongs to the true data distribution. $E_{z\sim P_{z(z)}}\left[log\left(1-D\big(G(z|c)\big)\right)\right]$ represents the discriminator's loss on generated samples, reflecting its ability to identify whether the generated sample $\bar{x}$ is fake. Therefore, the Conditional Generative Adversarial Network (cGAN) achieves optimal performance when the first term is maximized, and the second term is minimized.

2.2.3 Variational Autoencoder

A Variational Autoencoder (VAE) is a generative model based on probabilistic modeling in the latent space. The encoder $q(z|x)$ maps the input data x to the latent space z, while the decoder $p(x|z)$ reconstructs the data $\bar{x}$ from the latent space z.

The VAE algorithm is described as follows:

$$p(x,z) = p(x|z)p(z) \tag{7}$$

$$\begin{aligned}L(\theta,\phi;x) = E_{q(z|x)}[\log p_\theta(x|z)] - KL((z \mid x) \\ \parallel p_\varphi(z))\end{aligned} \tag{8}$$

Here, the data x is generated through the latent variable z, where $p(x|z)$ represents the decoder, and $p(z)$ is the prior probability of the latent variable. The posterior distribution is denoted as $p(z|x)$, and the approximate distribution is $q(z|x)$. The term $E_{q(z|x)}[\log p_\theta(x|z)]$ represents the reconstruction loss, which quantifies the error in reconstructing data x from the latent variable z. The term $KL((z \mid x) \parallel p_\varphi(z))$ is the KL divergence, which measures the difference between the variational distribution $q(z|x)$ and the prior distribution $p(z)$. Here, θ represents the decoder parameters, while ϕ denotes the encoder parameters.

2.2.4 Conditional vector projection

In the 2018 paper *"Spectral Normalization for Generative Adversarial Networks"*, Miyato et al. proposed conditional vector projection (CVP), a technique for Conditional Generative Adversarial Networks (cGANs). This method is primarily applied to the discriminator $D(x^*|c,\Theta_D)$ to effectively incorporate conditional information, thereby improving the model's discriminative capability and training stability. Conditional vector projection description:

$$f(x) = D_{feat}(x) \tag{9}$$

$$p(y|x) = f(x)^{\top} v_y \tag{10}$$

$$D(x, y) = f(x)^{\top} v_y + b \tag{11}$$

where, $D_{feat}(x)$ represents the feature extraction module of the discriminator. $f(x)$ is the feature representation of the input sample, v_y is the learnable embedding vector corresponding to class y, $p(y|x)$ introduces class information into the discriminator's decision function via inner product operation. b is a learnable bias term.

2.5 Self-attention mechanism

The self-attention mechanism is a window-size-independent method for learning long-range dependencies. It is widely used in Natural Language Processing (NLP) and Computer Vision (CV) tasks. Given an input sequence $X \in R^{n\times d}$, where n is the sequence length and d is the feature dimension, the self-attention mechanism computes weighted relationships among Query (Q), Key (K), and Value (V) to generate new feature representations, enabling the learning of long-range dependencies.

3. ALGORITHM INNOVATION

Based on the theoretical research and applied innovations, this paper proposes the Variational Autoencoder (VAE) algorithm based on a self-attention mechanism adaptively (VAE based on SAM), a self-adaptive encoding method integrating self-attention and conditional vector projection (self-adaptive EM), and the Multi-metric Weighted Evaluation Algorithm (mmWVEA). These algorithms address the problems of generating monotonous samples, imperfect coding techniques, and a simplistic evaluation system in traditional generative adversarial neural networks.

3.1 Variational Autoencoder (VAE) algorithm based on a self-attention mechanism adaptively (VAE based on SAM)

Integrating the self-attention mechanism into the encoding-decoding module of the VAE algorithm enables the improved VAE to learn long-range dependencies of objects. The flowchart of the VAE based on SAM algorithm is shown in Figure 1.

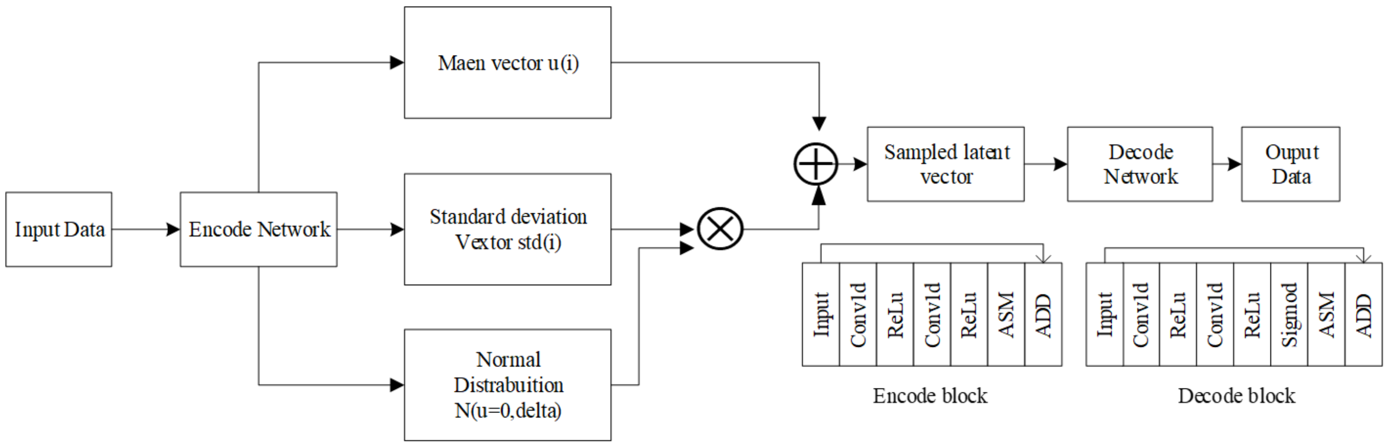

Figure 1. Flowchart of the VAE based on SAM algorithm

3.2 The self-adaptive encoding method integrating self-attention and conditional vector projection (self-adaptive EM)

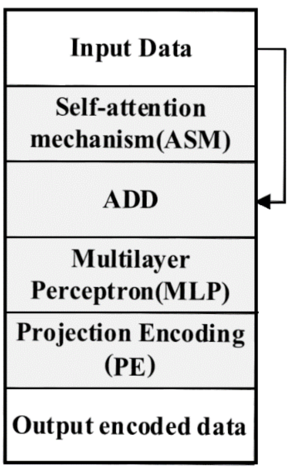

Figure 2. The flowchart of self-adaptive EM

To address the issues of singular conditions and weak constraint capability in conditional GAN (cGAN) networks, "The self-adaptive encoding method integrating self-attention and conditional vector projection" is proposed. This method incorporates the projection of class-conditional information into the discriminator's decision function, thereby enhancing its ability to differentiate between generated and real samples and effectively improving the resolution and class consistency of the generated images. Furthermore, the self-attention mechanism learns the long-range dependencies between the condition set CCC and the input data, establishing a dependency between the generated data and the condition set. The flowchart of self-adaptive EM is shown in Figure 2.

In here, ASM Learn long-range dependencies feature in data through self-attention mechanism (ASM); Multilayer Perceptron (MLP) built the data-dependent distribution p(x); Establishing the association between conditional information and sample data through projection operation. Through the above three steps, the adaptive encoding algorithm learns the dependency distribution patterns of the input data and achieves adaptive encoding.

The algorithm pseudocode is represented in Table 1.

Table 1. The algorithm pseudocode

Input: Training sample dataset X

Processing procedure:

1.Long-range dependencies $P_{independence}(x)$ Learn in training sample dataset X through self-attention mechanism (ASM)

$$P_{independence}(x) = ASM(X)\text{+X}$$

2.The data-dependent distribution $p(x)$ is built by the Multilayer Perceptron (MLP).

$$p(x) = MLP(P\_independence(x))$$

3.Establishing the association between conditional information and sample data through projection encode operation

$$s = \langle h(x), c_{embed} \rangle = \langle X(i), p(x) \rangle$$

Output: Output encoded data

3.3 The Multi-metric Weighted Evaluation Algorithm (mmWVEA)

In generative adversarial neural network methods, commonly used evaluation metrics include Fréchet Inception Distance (FID), CCS, and Kullback-Leibler Divergence (DKLD_{KL}). FID measures the quality and diversity of generated samples by computing the distribution discrepancy between generated and real data in a high-dimensional feature space. CCS evaluates whether the generated samples are consistent with the input conditions. It focuses on the model's conditional dependency, ensuring that the generated output accurately reflects the input conditions. KLD quantifies the similarity between a distribution P(x) and another distribution Q(x). Since each evaluation metric only focuses on a specific aspect of performance, to comprehensively assess the effectiveness of the proposed algorithm, we construct the Multi-metric Weighted Evaluation Algorithm (mmWVEA), which is mathematically described as follows:

$$index(e) = \lambda_1 FID + \lambda_2 CCS + \lambda_3 D_{KL} \quad (12)$$

$$FID = \| \mu_r - \mu_g \|^2 + Tr(\Sigma r + \Sigma g - 2(\Sigma r \Sigma g)^{1/2}) \quad (13)$$

$$CCS = \frac{1}{N} \sum_{i=1}^{i=N} \prod(\hat{c}_i = c_i) \quad (14)$$

$$\mathrm{D_{KL}}(\mathrm{P} \parallel \mathrm{Q}) = \sum_{\mathrm{x}} \mathrm{P(x)} \log \frac{\mathrm{P(x)}}{\mathrm{Q(x)}} \quad (15)$$

$$\lambda_1 + \lambda_2 + \lambda_3 = 1 \quad (16)$$

$$\lambda_i = \frac{Val(i)}{(FID + CCS + D_{KL}(P \parallel Q))} \quad (17)$$

In here, $Val(i) \in \{FID, CCS, D_{KL}\}$.

Therefore, the pseudocode implementation of the Multi-metric Weighted Evaluation Algorithm is shown in Table 2.

Table 2. Pseudo-code of the evaluation function

Input: Training sample dataset X

Processing procedure:

1. The mean and covariance matrix of the real data feature distribution (μ_r, Σ_r) and the mean and covariance matrix of the generated data feature distribution (μ_g, Σ_g) are computed. The Fréchet Distance (i.e., Wasserstein-2 Distance) between these two distributions is then calculated.

$$FID = \| \mu_r - \mu_g \|^2 + Tr(\Sigma r + \Sigma g - 2(\Sigma r \Sigma g)^{1/2})$$

2. The generator G receives the condition cc and random noise z, generating a sample $\mathrm{x = G(z|c)}$. Meanwhile, a conditional discriminator C is assumed to exist, which outputs the predicted condition $\hat{c}$. The CCS value is then computed.

$$CCS = \frac{1}{N} \sum_{i=1}^{i=N} \prod(\hat{c}_i = c_i)$$

3. Compute the probability distributions of the generator P(x) and the discriminator Q(x), then calculate their Kullback-Leibler (KL) divergence.

$$\mathrm{D_{KL}}(\mathrm{P} \parallel \mathrm{Q}) = \sum_{\mathrm{x}} \mathrm{P(x)} \log \frac{\mathrm{P(x)}}{\mathrm{Q(x)}}$$

4. Adaptive Weight Calculation (λ_i)

$$\lambda_i = \frac{Val(i)}{(FID + CCS + D_{KL}(P \parallel Q))}$$

5. Integrated Evaluation Metric Calculation. Calculate the integrated evaluation metric based on FID, CCS, and D_{KL}

$$index(e) = \lambda_1 FID + \lambda_2 CCS + \lambda_3 D_{KL}$$

Output: Output *index(e)*

3.4 Conditional Generative Adversarial Network based on self-attention mechanism and VAE algorithm (adaptive cGAM-SAN-VAE)

To address the problems of generating monotonous samples, imperfect coding techniques, and a simplistic evaluation system in traditional generative adversarial neural networks. "Conditional Generative Adversarial Network Based on self-attention mechanism and VAE Algorithm (self-adaptive EM)" is proposed, this algorithm integrates the Variational Autoencoder (VAE) algorithm based on a self-attention mechanism adaptively (VAE based on SAM), a self-adaptive encoding method integrating self-attention and conditional vector projection (self-adaptive EM), and the Multi-metric Weighted Evaluation Algorithm (mmWVEA). The flowchart of adaptive cGAM-SAN-VAE is shown Figure 3.

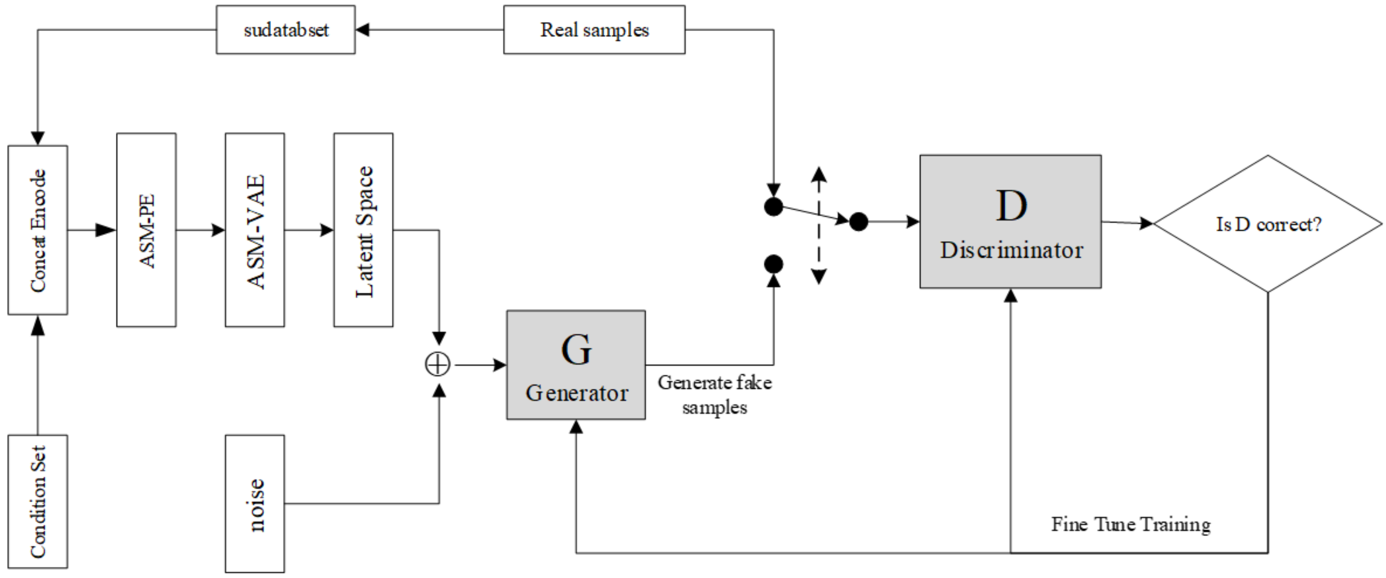

Figure 3. The flowchart of self-adaptive EM

4. EXPERIMENTS AND EXPERIMENTAL RESULTS ANALYSIS

4.1 Dataset introduction

The custom dataset self-DataSet in this paper has the following attributes. (1) It contains financial data from a university with typical time-series characteristics. (2) The continuous data collection period is t∈[2015.01.01,2024.12.30]. (3) The dataset consists of 7,236 entries. (4) The Conditional Label Dataset includes 21 labels related to university financial attributes, some of which are classified. All experiments in this paper were conducted on this dataset.

4.2 Algorithm ablation experiment

4.2.1 Ablation experiment macro features

The proposed algorithm is an integration of three innovative algorithms. Therefore, the algorithm ablation experiment fundamentally validates the effectiveness and advantages of this integration. On self-DataSet, ablation experiments based on the three innovative algorithms are conducted, and the effectiveness and advantages of the proposed algorithm are evaluated using Precision, Recall, and Index (e) as evaluation metrics.

Table 3. Algorithm ablation experiment results table

Ablation	**Algorithm**				**Evaluation Metrics**		
	GAN	cGAN	ASM-PE	ASM-AVE	Precision (%)	Recall (%)	Normalized Index (e)
1	√				82.37	78.73	0.16
2		√			84.25	83.62	0.35
3		√	√		91.47	87.35	0.57
4		√		√	93.84	90.78	0.64
5		√	√	√	97.37	92.93	0.78

Experimental Results Analysis: As shown in the Table 3, as the ablation experiment progresses, the integration of algorithms in the proposed method increases, leading to a gradual improvement in algorithm performance. The Precision metric steadily improves, indicating an enhancement in the quality and diversity of generated samples. Meanwhile, the Recall metric also increases, suggesting a reduced probability of mode collapse. Therefore, the ablation experiment demonstrates that the proposed algorithm is effective and exhibits superior performance.

4.2.2 Performance comparison of ablation experiment in microscopic data generation

The previous analysis has validated the macroscopic effects of the ablation experiment, confirming the effectiveness and performance advantages of the proposed algorithm. To further investigate the relationship between the ablation experiment and microscopic data generation, ablation experiments based on the three innovative algorithms are conducted on the self-DataSet. The effectiveness and advantages of the proposed algorithm in microscopic data generation are evaluated using the following metrics: Mean ratio $\gamma_1 = \frac{\mu_1}{\mu_2}$, Variance ratio $\gamma_2 = \frac{\delta_1}{\delta_2}$, Skewness ratio $\gamma_3 = \frac{s_1}{s_2}$ and Kurtosis ratio $\gamma_4 = \frac{k_1}{k_2}$. For consistency in comparison, γ_1 is computed as follows: $\gamma_1 = \begin{cases} \frac{\mu_1}{\mu_2} & \mu_1 \le \mu_2 \\ \frac{\mu_1}{\mu_2} & \mu_1 \ge \mu_2 \end{cases}$. And similarly, γ_2, γ_3, and γ_4 are calculated using the same approach.

Table 4. Ablation experiment microscopic effect table

Ablation	Algorithm				Evaluation Metric			
	GAN	cGAN	SAM-PE	ASM-AVE	γ_1	γ_2	γ_3	γ_4
1	√				≤0.56	≤0.32	≤0.41	≤0.24
2		√			≤0.63	≤0.45	≤0.47	≤0.35
3		√	√		≤0.75	≤0.57	≤0.62	≤0.59
4		√		√	≤0.66	≤0.63	≤0.86	≤0.79
5		√	√	√	≤0.96	≤0.89	≤0.88	≤0.92

Experimental Results Analysis: As shown in Table 4, with the continuous integration of algorithms, all four evaluation metrics gradually increase and approach 1. This linear trend indicates that the proposed algorithm progressively generates samples that approximate real samples in the process of microscopic data generation. Consequently, the results demonstrate that the proposed algorithm is more effective in generating microscopic data, directly proving its effectiveness and comparative advantage.

4.3 Algorithm performance comparison

To verify the advantages of the proposed algorithm, a comparative experiment was conducted under the same experimental conditions between the proposed algorithm and GAN, cGAN, AM-cGAN, and Encode-cGAN methods. The experimental results are shown in Table 5.

Experimental Results Analysis: The experimental data in Table 5 indicate that, under the same experimental conditions, the proposed algorithm achieves better comparative performance advantages compared to the listed algorithms. This is because the proposed algorithm effectively addresses the following three issues present in the current cGAN through its three sub-algorithms: (1) The problem of generating monotonous samples. (2) The issue of imperfect coding techniques. (3) The problem of a simplistic evaluation system.

Table 5. Algorithm performance comparison

Algorithm		Signal Attribute Comparison and Analysis			
		γ_1	γ_2	γ_3	γ_4
GAN		≤0.56	≤0.32	≤0.41	≤0.24
cGAN		≤0.63	≤0.45	≤0.47	≤0.35
AM-cGAN	Dot-Product Attention [27]	≤0.59	≤0.47	≤0.52	≤0.46
	Positional Encoding [28]	≤0.63	≤0.45	≤0.56	≤0.48
	SAM	≤0.75	≤0.57	≤0.62	≤0.59
Encode-cGAN	Encode 1 [29]	≤0.69	≤0.62	≤0.78	≤0.66
	Encode 2 [30]	≤0.73	≤0.72	≤0.72	≤0.71
	cGAN +SAM-PE	≤0.75	≤0.57	≤0.62	≤0.59
The proposed		≤0.96	≤0.89	≤0.88	≤0.92

5. CONCLUSION AND OUTLOOK

To address the following three issues present in the current cGAN: (1) Generating monotonous samples; (2) Imperfect coding techniques; (3) Simplistic evaluation system, this paper proposes the "Conditional Generative Adversarial Network Based on self-attention mechanism and VAE Algorithm and Its Applications". This algorithm integrates three customized sub-algorithms, effectively solving the above problems. The proposed algorithm is validated on a self-defined university financial dataset, and the experimental results demonstrate its feasibility and comparative advantages.

Future Research Directions

1. Data Expansion: Utilize a larger dataset to further investigate and validate the feasibility and comparative advantages of the proposed algorithm.
2. Attention Mechanism Optimization: Explore attention mechanisms tailored to the characteristics of the dataset to enhance algorithm performance.

ACKNOWLEDGMENT

This work is supported by The Introduce intellectual resources Projects of Hebei Province of China in 2023 (The depth computing technology of double-link based on visual selectivity, Grant No.: 2060801); The Introduce intellectual resources Projects of Hebei Province of China in 2025 (3D Point Cloud Segmentation Technology Based on Graph Convolution Algorithm; Key Technologies of Audio Generation Based on Improved Adversarial Neural Networks); The Key R&D Projects in Hebei Province of China (Grant No.: 19210111D); The Special project of sustainable development agenda innovation demonstration area of the R&D Projects of Applied Technology in Chengde City of Hebei Province of China (Grant Nos.: 202205B031, 202205B089, 202305B101, 202404B104); Higher Education Teaching Reform Research Projects of National Ethnic Affairs Commission of the People's Republic of China in 2021 (Grant No.: 21107, 21106); Wisdom Lead Innovation Space Projects (Grant No.: HZLC2021004).

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