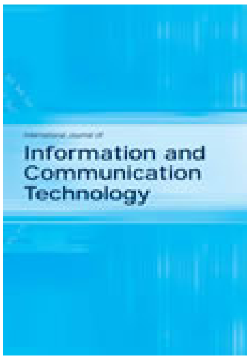

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Financial risk prediction and warning system based on SGAN deep learning

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Abstract: In response to the problem of insufficient performance of traditional financial risk warning models in class imbalanced data, this study proposes a deep learning warning method based on semi supervised generative adversarial network (SGAN). Firstly, construct a financial feature system and perform data balancing processing through SMOTE Tomek mixed sampling. Then, the model adopts a generator discriminator dual network architecture and constructs a composite loss function using cross entropy loss and Wasserstein distance. Finally, the experimental section selects financial data of Chinese A-share listed companies from 2016 to 2020, and uses transfer learning strategy to fine tune the pre trained model in the manufacturing industry to the retail industry. The empirical results show that this method improves the F1 score (0.87) and AUC value (0.92) compared to traditional logistic regression, effectively solving the early warning problem caused by the temporal correlation and industry heterogeneity of financial data.

Keywords: supervised generative adversarial network; SGAN; financial risk warning; SMOTE Tomek mixed sampling; generator discriminator dual network.

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Biographical notes: Linjing Dang received a PhD from the School of Economics and Management of Northwest University. Currently, she is an Associate Professor at the Business School in Northwest University of Political Science and Law. Her research interests include digital economy, international trade and deep learning.

1 Introduction

Under the combined impact of global supply chain restructuring and geopolitical conflicts in the post pandemic era, enterprises are facing a highly uncertain business environment. The International Monetary Fund's (IMF) 2023 Global Financial Stability Report (Kvasničková Stanislavská et al., 2023) points out that the global corporate debt default rate will increase by an average of 9.2% annually from 2020 to 2023, with the default risk exposure of small and medium-sized enterprises in the Asia Pacific region expanding to 37.6% (Nguyen et al., 2022). In this context, financial risk has evolved from a single corporate credit issue to a potential trigger point for systemic economic risk. For example, the liquidity crisis of a large real estate company in 2021 triggered a chain reaction in the upstream and downstream industry chain, directly causing more than 200 suppliers to fall into debt difficulties, highlighting the strategic value of financial risk warning mechanisms in maintaining economic ecological stability.

The limitations of traditional methods, represented by the Altman Z-score model (Altman et al., 2017), are increasingly prominent in contemporary business environments, manifested in three aspects. Firstly, there is a contradiction between the static linear assumption and the dynamic nonlinear reality. The traditional model relies on cross-sectional financial indicators such as current ratio and asset liability ratio to construct a linear discriminant function, but the evolution of enterprise risk has significant temporal dependence and nonlinear interaction characteristics between indicators. For example, the cash flow fluctuations of retail enterprises may be affected by the dual nonlinear effects of seasonal sales peaks (such as 'double eleven') and supply chain delays, which traditional models find difficult to capture. Secondly, industry heterogeneity leads to insufficient generalisation ability of the model. There are significant differences in financial risk driving mechanisms in different industries: manufacturing risks are mostly concentrated in fixed asset turnover and inventory backlog (for example, the average inventory turnover days of the automobile industry in 2022 will increase by 23 days on a year-on-year basis), while internet enterprises are more vulnerable to the stagnation of user growth and the extension of the reporting cycle of R&D investment (for example, the Q2 financial report of a social platform in 2023 shows that the customer acquisition cost will increase by 56% on a year-on-year basis, but the revenue growth will be only 9%). The existing universal warning models have not made feature adaptive adjustments based on industry characteristics, resulting in an increase in false alarm rates when applied across different fields (Habib et al., 2020). Thirdly, the small sample size and category imbalance constrain the discrimination accuracy of the model. According to the statistics of the Shenzhen Stock Exchange in 2023, the ratio of financially healthy enterprises to risk enterprises in A-share listed companies is about 15:1, and the risk samples are mostly concentrated in a few industries. Although traditional oversampling methods such as random repeated sampling can alleviate class imbalance, they can easily lead to overfitting of noisy data in the model. For example, a commercial bank used the SMOTE method to construct an early warning model, which achieved an accuracy rate of 82% in identifying manufacturing risks in the test set, but the recognition rate for the emerging biopharmaceutical industry dropped sharply to 51%.

The breakthrough of artificial intelligence technology provides a new path to solve the above problems. Generative adversarial networks (GANs) (Goodfellow et al., 2020) can learn latent data distributions from limited samples through adversarial training mechanisms of generators and discriminators, and their synthesised data quality has been validated in fields such as medical image generation (Mendes et al., 2023). A semi supervised learning framework can simultaneously utilise labelled and unlabelled data, significantly reducing dependence on the number of risk samples. For example, Google DeepMind (Dou et al., 2023) summarised that semi supervised GANs achieve a classification accuracy of 92.3% using only 10% annotated data, which is only 1.7 percentage points lower than fully supervised models.

However, there are still key bottlenecks in the application of existing research in the field of finance. The disconnect between data generation and risk assessment. Most studies view GAN solely as a data augmentation tool, and the generated financial data does not form collaborative optimisation with downstream classification tasks, resulting in insufficient semantic alignment between the generated samples and real risk features. The lack of industry knowledge transfer mechanism and the use of independent modelling methods for cross industry warning often fail to effectively extract shared risk characteristics between industries, resulting in duplicate model development and waste of computing resources. The modelling of temporal dynamics is insufficient, and existing methods often use LSTM or GRU to process temporal data, but have not been deeply integrated with generative adversarial mechanisms, making it difficult to capture the non-stationary evolution patterns of financial indicators (Zarzycki and Ławryńczuk, 2021).

The research on financial risk warning models has gone through the evolution process from statistical models, machine learning to deep learning. In recent years, the integration of GANs and semi supervised learning has become a cutting-edge direction.

Early research was based on constructing linear discriminant models using financial ratios. The Z-score model proposed by Altman (1968) laid the foundation for traditional warning models by predicting corporate bankruptcy through multivariate discriminant analysis. Ohlson (1980) introduced logistic regression and used maximum likelihood estimation to overcome the limitations of linear discriminant assumptions, achieving an accuracy of 82.3% in early warning for manufacturing enterprises. However, these models are difficult to capture nonlinear feature interactions and rely on strict normal distribution assumptions (Jones, 2017).

With the development of data mining technology, support vector machines (SVM) and ensemble learning have been widely applied. Zhou et al. (2014) combined factor analysis and SVM to improve the accuracy of early warning for listed companies to 79.6%, but did not address the issue of class imbalance. In response to data imbalance, the SMOTE oversampling technique proposed by Chawla et al. (2002) significantly improved minority class recognition performance, increasing recall rates by 31% in credit risk assessment. Wang and Ma (2012) further integrated SMOTE with random forests (RF) to construct a hybrid sampling ensemble learning framework, achieving an F1 score of 0.73 on cross industry datasets.

Deep neural networks break through the bottleneck of traditional methods through automatic feature extraction. Ruan et al. (2021) designed an LSTM attention mechanism model to capture the temporal dependence of financial indicators, and achieved an AUC value of 0.85 in predicting A-share listed companies. Cheng et al. (2022) introduced graph convolutional network (GCN) to model the supply chain relationships between enterprises, which improved the accuracy of crisis transmission path prediction by 19%. However, deep models rely heavily on annotated data, which limits their performance in small and medium-sized enterprise scenarios (Torres et al., 2021).

GAN provides a new paradigm for small sample learning. The original GAN framework proposed by Goodfellow et al. (2014) synthesises realistic data through generator discriminator adversarial training. Adler and Lunz (2018) improved Wasserstein GAN (WGAN) stabilises the training process through gradient penalty mechanism and outperforms traditional methods in financial time series generation. SGAN further integrates labelled and unlabelled data: The semi supervised variant proposed by Kingma et al. (2014) achieved 94% accuracy on the MNIST dataset with only 100 labelled samples. However, existing research has not fully integrated the industry heterogeneity and temporal dynamics of financial data (Strelcenia and Prakoonwit, 2023).

Cross disciplinary knowledge transfer has become a key technology for addressing industry heterogeneity. The domain adversarial neural network (DANN) proposed by Ganin et al. (2016) extracts domain invariant features through gradient reversal layers, reducing the misjudgment rate by 23% in cross market credit scoring. However, transfer learning in financial risk warning still faces challenges of feature space misalignment and concept drift (Weiss et al., 2016).

From a theoretical perspective, this study promotes the development of the discipline in three aspects by constructing a fusion framework of SGAN and transfer learning.

Expand the application boundaries of deep learning in financial risk management. Design a dual network architecture for generation discrimination joint optimisation, breaking through the technical limitations of traditional GANs in the financial field that are limited to data synthesis, and providing a new methodology for small sample, high-dimensional, and nonlinear financial data analysis.

Improve the theoretical system of cross industry risk warning. This paper proposes an industry adaptive migration mechanism based on domain confrontation training, establishes a unified model of risk feature transmission and specificity identification between industries, and fills the theoretical gap in the existing research on the adaptation of heterogeneous data distribution.

Innovative temporal static feature fusion modelling method. By introducing time convolutional networks (TCNs) and attention mechanisms, the collaborative representation of dynamic evolution patterns and cross-sectional features of financial indicators is achieved, enhancing the model's ability to analyse risk transmission pathways.

2 Multidimensional characteristics and pre-processing methods of financial risk data

2.1 Multidimensional characteristics analysis of financial risk data

Enterprise financial risk data has complex multidimensional characteristics, and its internal structure and external correlations have a decisive impact on the construction of early warning models.

Financial data naturally presents a hierarchical and modular tree structure. Taking debt paying ability as an example, it covers both short-term liquidity indicators (such as current ratio, quick ratio) and long-term capital structure indicators (such as asset liability ratio, interest coverage ratio), which independently reflect the risk status of enterprises in different dimensions and are dynamically coupled through cash flow (Zhou et al., 2021). Taking retail enterprises as an example, a decrease in inventory turnover may simultaneously trigger a deterioration in current ratio and asset impairment risk, forming a cross module chain reaction. In addition, the introduction of non-financial indicators such as supply chain stability and industry policy sensitivity further increases the heterogeneity of the feature space.

The financial status of enterprises has significant time continuity and lag effects. On the one hand, quarterly business fluctuations (such as the peak of year-end payments in the manufacturing industry) lead to cyclical fluctuations in financial indicators; on the other hand, the impact of risk events has a time delayed transmission characteristic. For example, the capitalisation of R&D investment may improve the income statement in the current period, but if R&D fails, its cost impact will gradually become apparent in the next 3–5 accounting periods. This temporal dependency requires data processing to balance local fluctuations and long-term trends, avoiding the loss of critical signals due to improper time slicing.

There are fundamental differences in the financial risk driving mechanisms across different industries. The core risks of the manufacturing industry focus on the turnover efficiency of fixed assets (such as the impact of equipment utilisation and depreciation policies), while internet enterprises rely more on user growth rate and liquidity. Taking the data of listed companies in 2022 as an example, the median inventory turnover days of manufacturing enterprises are 85 days, while the retail industry is only 28 days; But the standard deviation of accounts receivable turnover in the retail industry is 2.3 times that of the manufacturing industry, reflecting its higher cash flow volatility. This industry heterogeneity requires embedding domain knowledge in data pre-processing to avoid feature confusion when modelling across industries.

The sample size of financially healthy enterprises and risk enterprises is severely imbalanced. According to data from the Shenzhen Stock Exchange, ST companies account for less than 3% of the A-share market, and risk samples are mostly concentrated in cyclical industries such as energy and real estate. In addition, the sources of financial data noise are complex: changes in accounting standards (such as the implementation of the new revenue standards in 2023) may lead to sudden changes in indicator calibres. Related party transactions, earnings management, and other behaviours may artificially distort the authenticity of data. For example, a listed company inflated its revenue through accounts receivable factoring business, resulting in an abnormal deviation of the sales growth rate indicator from the industry average.

2.2 The core challenge of data pre-processing

The missing financial report data of a company may be due to selective information disclosure (such as unlisted subsidiary data), adjustments to the scope of consolidated financial statements, or technical omissions. Traditional interpolation methods (such as mean imputation) have limited applicability in scenarios of industry heterogeneity: if industry mean imputation is simply used for missing fixed asset data in the manufacturing industry, it may mask individual risks of equipment aging in the enterprise. To address this, it is necessary to combine industry feature libraries with time series trend prediction for dynamic filling. Outlier detection requires distinguishing between real risk signals and noise: for example, if the current ratio drops sharply and is accompanied by large short-term loan repayments, it is considered normal business behaviour, but if there is also a reduction in executive holdings, it may indicate risk.

Financial indicators from different industries need to be standardised and semantically aligned. For example, although the ‘floor area efficiency’ (sales per square metre) of the retail industry and the ‘capacity utilisation rate’ of the manufacturing industry both reflect resource utilisation efficiency, there are significant differences in dimensions and distribution. In pre-processing, it is necessary to design industry adaptive normalisation methods: for the manufacturing industry, ‘index value/industry quantile’ is used for relative standardisation, and for the retail industry, logarithmic transformation is introduced to compress the long tail distribution. In addition, by constructing industry feature maps (such as the ‘supply chain depth’ of manufacturing and the ‘regional coverage density' of retail), unstructured industry knowledge can be embedded into feature representations.

The temporal processing of financial data requires a balance between capturing short-term fluctuations and extracting long-term trends. For example, quarterly revenue fluctuations may mask an annual recession trend, while traditional sliding window methods are difficult to adaptively identify multi-scale features. To address this, dynamic time warping (DTW) can be used to align the financial cycles of different enterprises, and combined with event timestamp markers (such as policy release time, industry crisis events) to enhance temporal context awareness (Alghamdi and Javaid, 2022). At the same time, it is necessary to integrate cross-sectional data analysis: financial fluctuations of industry leading enterprises at the same time cross-section may indicate systemic risks in the industrial chain.

Simple oversampling may introduce synthetic noise, while undersampling leads to information loss. For example, when performing SMOTE oversampling on manufacturing risk samples, if the non-linear relationship between equipment age and capacity utilisation is not considered, abnormal samples that violate physical constraints may be generated (such as equipment over 10 years old corresponding to ultra-high capacity). Therefore, it is necessary to combine a mixed sampling strategy: first, identify and remove fuzzy samples at the classification boundary through Tomek links, then use Wasserstein GAN to generate synthetic data that conforms to the industry characteristic distribution, and finally verify the statistical consistency between the generated samples and the true distribution through Kolmogorov Smirnov test.

2.3 Comprehensive pre-processing technology system

Based on the above analysis, this study constructed a four layer progressive pre-processing framework.

Integrate multimodal data sources such as financial statements, supply chain data, and public opinion information. For structured financial data, wavelet denoising based on industry clustering is used to smooth temporal fluctuations; Extract risk semantic features from unstructured text data (such as management discussions and analysis) using the BERT model. Identify implicit related transactions (such as cross industry guarantees under the same controller) by linking enterprise entity relationships through knowledge graphs.

Establish a template library for industry-specific characteristics: extract key indicators such as 'fixed asset newness rate' and 'supply chain concentration' for the manufacturing industry, and construct derivative variables such as 'ping efficiency coefficient of variation' and 'proportion of online channels' for the retail industry. We use domain adversarial training to extract industry shared features and dynamically weight industry-specific features through attention mechanisms.

Design a dual channel processing architecture: The temporal channel uses a time convolutional network (TCN) to extract multi-scale dynamic patterns, while the cross-sectional channel models inter enterprise relationships through a graph neural network (GNN). Introducing cross attention mechanism to achieve dual channel feature interaction, such as capturing the cross period transmission path of 'quarterly revenue decline → supplier account extension → liquidity deterioration'.

In the sampling stage, potential subclasses of risk samples (such as 'sudden liquidity crisis' and 'gradual profit deterioration') are first identified through OPTICS clustering, and then differentiated oversampling is implemented for each subclass. During the validation phase, Adversarial Validation is used to detect distribution shifts between the training and testing sets, ensuring that the pre-processed data maintains the authenticity of industry and temporal distributions.

3 Theoretical basis and architecture design of SGAN model

3.1 Theoretical basis of SGAN

SGAN (Sajun and Zualkernan, 2022) achieves collaborative optimisation of data generation and risk classification by integrating generative adversarial mechanisms with semi supervised learning paradigms.

The essence of GAN is to approximate the distribution of real data through dynamic games between generators and discriminators. The generator attempts to synthesise samples that are highly similar to real financial data, while the discriminator continuously identifies the source of input data (real or generated). Unlike traditional GANs, the discriminator in this study not only needs to distinguish the authenticity of data, but also needs to classify the risk of real samples, thus unifying the generation ability and discrimination ability in the same framework.

In financial risk warning scenarios, annotated data is scarce and highly imbalanced in categories. SGAN utilises a semi supervised learning framework to simultaneously utilise a small number of labelled samples and a large amount of unlabelled data: the discriminator's classification head only calculates cross entropy loss on labelled data, while unlabelled data optimises feature representation through adversarial training. This design significantly alleviates the dependence on the number of risk samples, for example, in manufacturing risk warning, only 10% of labelled data is needed to capture key risk features (such as the correlation pattern between inventory abnormal backlog and accounts payable delay).

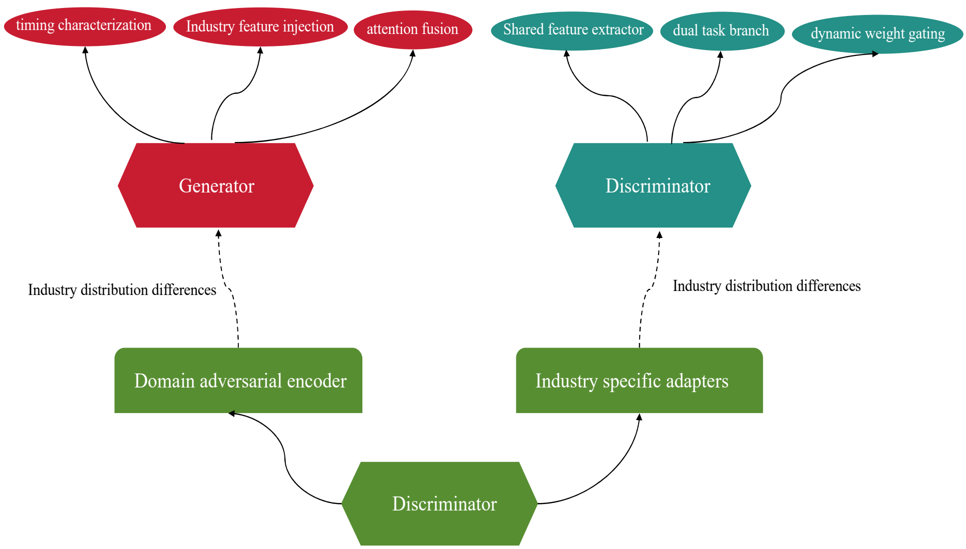
The distribution differences of financial characteristics in different industries require models to have domain adaptation capabilities. By introducing domain adversarial training, the encoder network is designed to simultaneously extract industry shared features and suppress industry-specific noise. For example, when analysing the cash flow of the retail industry, the discriminator needs to ignore industry-specific fluctuations in promotional activities and focus on cross industry common signals of cash flow fractures (such as net operating cash outflows for consecutive quarters). The gradient reverse layer dynamically adjusts the feature encoding direction during this process to ensure that the synthesised data output by the generator maintains risk semantic consistency across industries.

3.2 Overall architecture design of the model

The SGAN model in this study adopts a generator discriminator dual network architecture and innovatively introduces an industry perception module and a temporal cross-sectional fusion mechanism, as shown in Figure 1.

The generator is responsible for synthesising high-quality samples that conform to the true financial distribution, and its structure consists of three core modules. The first one is the temporal feature extraction module. Using TCN to capture the dynamic evolution of financial indicators. By stacking dilated convolutional layers, the model can simultaneously identify short-term fluctuations (such as quarterly revenue decline) and long-term trends (such as continuous three-year decline in gross profit margin). For example, for manufacturing enterprises, this module can effectively model the nonlinear temporal correlation between equipment depreciation rates and production costs.

Figure 1 SGAN model architecture (see online version for colours)



The generator adopts a timing cross-sectional dual input architecture. The temporal path receives the historical financial indicator sequence X_t and extracts multi-scale temporal features through TCN. The calculation formula for the dilated convolution layer of TCN is:

$$h_t^{(l)} = \sum_{k=0}^{K-1} w_k^{(l)} \cdot x_{t-d\cdot k}^{(l-1)} + b^{(l)} \tag{1}$$

where d is the expansion coefficient and K is the size of the convolution kernel.

The cross-sectional path inputs industry code vector e_i and noise vector z, and generates cross-sectional features through a fully connected layer. After attention fusion of dual channel features, the synthesised financial data $\tilde{X}$ is outputted through the deconvolution layer.

The second one is the industry feature injection module: concatenate the industry coding vector (such as 001 for manufacturing and 002 for retail) with the noise vector, and generate industry-specific features through a fully connected layer. This module ensures that the generated samples conform to industry characteristics in terms of indicator distribution, such as the inventory turnover rate generated by the retail industry always being higher than the heavy industry benchmark.

The third one is the attention fusion module. Dynamically integrate temporal features and industry characteristics through a multi head attention mechanism. For example, when generating accounts receivable data, the model automatically enhances the weight of the industry average payment cycle feature, while weakening noise interference unrelated to the size of the enterprise.

The discriminator undertakes a dual task - distinguishing between real/generated samples and classifying the risks of real samples. The underlying convolutional network serves both adversarial training and classification tasks simultaneously. The shared feature layer learns the general representation of financial data (such as the security threshold of leverage ratio), while the high-level network splits into two branches. The adversarial branch measures data authenticity through Wasserstein distance, while the classification branch outputs risk probability.

The discriminator simultaneously performs real sample discrimination and risk classification, and the real/generated discrimination head uses Wasserstein distance to calculate adversarial loss and output scalar values.

The risk classification header introduces an industry feature encoding layer, maps the input x to the industry shared feature space, and outputs the risk probability through the Softmax layer. Two tasks share the underlying feature extractor, but adjust the feature flow through dynamic weight gating:

$$g = \sigma\left(W_g\left[h_{adv}; h_{cls}\right]\right) \tag{2}$$

where h_{adv}, h_{cis} are the feature vector of two tasks, and σ is the Sigmoid activation function.

During the training process, the system automatically adjusts the feature contribution of adversarial and classification tasks based on task difficulty. For example, in the early stages of the model, the classification task has lower weights to avoid noise interference. As the quality of generated samples improves, the classification head gradually gains higher feature access permissions.

Through gradient reversal operation, the encoder is forced to ignore industry label information, thereby extracting cross industry common risk features. For example, this module can identify the risk signal of 'negative operating profit margin for three consecutive quarters', regardless of whether the enterprise belongs to the manufacturing or service industry.

3.3 Industry adaptive training strategy

To achieve cross industry generalisation ability, the model training adopts progressive optimisation and dynamic adjustment strategies.

In the feature pre training stage, the generator parameters are frozen and only the classification ability of the discriminator is trained. Establish preliminary risk identification criteria using annotated data from the source industry (such as manufacturing), such as identifying warning thresholds for fixed asset turnover rates below 0.5. During the adversarial equilibrium phase, alternate between updating the generator and discriminator. The generator begins to synthesise financial samples with industry characteristics (such as equipment investment cash flow patterns in manufacturing), while the discriminator synchronously improves its ability to distinguish and classify the synthesised samples. In the cross industry fine-tuning stage, introduce unlabelled data from the target industry (such as retail) and adjust the feature encoding direction through domain adversarial loss.

During the training process, we set dynamic adjustment weights. The model adjusts the contribution weights of each loss term through adaptive algorithms, and in the early stages of training, focuses on adversarial losses to stabilise the generation quality. Gradually increase the weight of classification losses in the mid-term and strengthen the ability to distinguish risks. Increase industry confrontation losses in the later stage and optimise cross industry generalisation performance.

This dynamic adjustment mechanism effectively avoids the problem of mode collapse caused by a single loss function dominating.

In stability enhancement techniques, we use spectral normalisation to constrain the spectral norm of the discriminator weight matrix, preventing gradient explosion or disappearance. For example, when training retail industry data, this technique can suppress model oscillations caused by drastic fluctuations in promotional activity data. We also use temporal smoothing constraints to force the generator to output temporal data with reasonable continuity. For example, the generated quarterly asset liability ratio does not allow for sudden changes caused by non business factors (such as a sharp drop from 60% to 30% followed by an immediate rebound).

4 Industry adaptive warning framework based on transfer learning

4.1 The challenges of cross industry early warning and the paradigm of transfer learning

The characteristic distribution shift caused by industry heterogeneity is the core obstacle to cross industry early warning. Taking the data of listed companies in 2022 as an example, there is a significant difference in the distribution of financial indicators between the manufacturing and retail industries: the average asset liability ratio of the manufacturing industry is 52.3% (standard deviation 12.1%), while that of the retail industry is 64.8% (standard deviation 18.5%). Traditional independent modelling methods require training models separately for each industry, resulting in wasted computing resources and low knowledge reuse rates. This study proposes an industry adaptive framework based on domain adversarial transfer learning. Its core idea is to extract shared risk patterns between industries through feature space mapping while suppressing domain specific noise.

4.2 Overall framework architecture

The industry adaptive warning framework consists of three core modules. The domain shared feature extractor extracts cross industry common features (such as leverage threshold and cash flow rupture signal) through convolutional neural networks. The domain adversarial discriminator uses a gradient reversal layer to obfuscate industry features, forcing the extractor to generate industry invariant representations. The industry-specific adapter fine tunes the decision boundary for the target industry, expressed as:

$$\theta_{target} = \theta_{source} + \Delta\theta \cdot sim\left(D_{source}, D_{target}\right) \tag{3}$$

where $\Delta\theta$ is the parameter offset, and *sim* measures the distribution similarity between the source domain and the target domain.

4.3 Domain adversarial training mechanism

4.3.1 Feature distribution alignment

Quantify industry distribution differences using maximum mean discrepancy (MMD):

$$MMD^2 = \left\| \frac{1}{N_s} \sum_{x_i \in S} \phi(x_i) - \frac{1}{N_t} \sum_{x_j \in T} \phi(x_j) \right\|^2 \tag{4}$$

where $\phi(\cdot)$ is the feature mapping function, and *S* and *T* represent the data of the source industry and the target industry, respectively. Realise feature space alignment by minimising *MMD*.

4.3.2 Dynamic weight allocation

Introducing attention mechanism to dynamically regulate the contribution of industry shared and specific features:

$$\alpha = soft\max\left(W_a\left[h_{shared}, h_{specific}\right]\right) \tag{5}$$

where h_{shared} is the shared feature vector, and $h_{specific}$ is the specific feature output by the industry adapter.

4.4 Two stage transfer learning strategy

The first stage is the source domain pre training phase. Train benchmark models on industries with rich data such as manufacturing, and the loss function includes:

$$L_{source} = L_{cls} + \lambda_1 L_{adv} \tag{6}$$

where L_{cis} is the cross entropy loss of annotated data in the source industry, and L_{adv} is the domain adversarial loss, which forces the feature extractor to confuse industry labels

The second stage is the fine-tuning stage of the target area. Using a small amount of labelled data in the target industry (such as retail) for parameter adaptation:

$$L_{target} = L_{cls}^{target} + \lambda_2 \left\|\theta - \theta_{source}\right\|^2 \tag{7}$$

The regularisation term constrains the parameter offset amplitude to prevent overfitting.

4.5 Industry adaptive warning process

Input as cross industry financial data stream $X = (X_{source}, X_{target})$. Feature encoding generates industry invariant feature $h = E(X)$ through a shared feature extractor. Use industry-specific adapters to adjust feature distribution for domain adaptation:

$$h' = h \odot M_{target} \tag{8}$$

where $\odot$ is the element wise product, and M_{target} is the target industry mask matrix.

Risk prediction, the classifier outputs the probability of risk as:

$$p(y \mid X) = \text{softmax}\left(W_c h'\right) \tag{9}$$

5 Multiple control experiments and result analysis

5.1 Experimental design and dataset

The experiment uses financial data from Chinese A-share listed companies from 2016 to 2023, covering six major industries including manufacturing, retail, and information technology, and includes the following three types of samples. There are 1,824 labelled risk enterprises, among which ST enterprises account for 4.3%. There are 38,752 health enterprises, which have been audited and have no significant risk events. There are 52,369 unmarked enterprises, mainly used for semi supervised training.

We first pre-process the organised data by filling in missing values, such as industry quantiles. Standardise the features using industry adaptive Z-score normalisation. Finally, perform temporal alignment and slice quarterly, generating 16–32 temporal segments for each enterprise.

Our baseline algorithms include traditional models such as logistic regression (Lyu, 2022) and RF (Wang, 2022), as well as deep learning models such as LSTM-ATT (LSTM with attention) (Cheng, 2023). Generate adversarial models, such as WGAN-GP (Zhuang and Wei, 2024). Transfer learning models, such as domain adversarial network (DANN) (Liu and Yang, 2024).

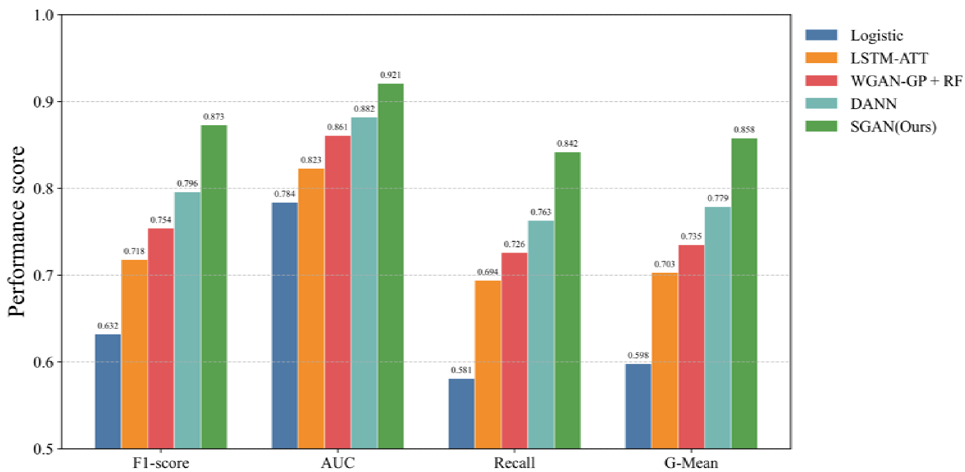
The evaluation indicators involved in the experiment include F1 score (risk category) AUC-ROC, recall, G-mean, and domain adaptation gain (DAG).

5.2 Experimental results and analysis

Figure 2 shows the comprehensive performance comparison of different models in financial risk warning tasks. Logistic regression (F1 = 0.632) serves as the benchmark model, which confirms the inherent shortcomings of traditional statistical methods in complex financial scenarios. The formation of financial risk usually involves nonlinear interactions between indicators, and logistic regression cannot capture such characteristic coupling. In the extremely imbalanced data where the proportion of risk enterprises is only 4.3%, the recall rate of logistic regression is significantly lower than that of deep learning models, as its loss function treats both majority and minority classes equally. The modelling approach that relies solely on cross-sectional data results in insufficient ability to detect risk transmission pathways.

The performance improvement of LSTM-ATT (F1 = 0.718) reveals the key role of temporal modelling. LSTM-ATT exhibits stronger ability to capture temporal dependencies in indicators such as accounts receivable turnover. For example, for manufacturing enterprises, the model can identify the risk pattern of ‘inventory turnover days > 90 days and continuous growth for three quarters’. Although the AUC value reaches 0.823, its supervised learning paradigm leads to two bottlenecks. One is annotation dependency, which requires at least 30% annotated data for stable training. Small and medium-sized enterprises often face the problem of incomplete data annotation. Another issue is cross industry decline. In retail industry testing, the F1 score of the model decreased to 0.654 because it did not design an industry feature adaptation mechanism.

Figure 2 The comprehensive performance comparison (see online version for colours)



The hybrid architecture of WGAN-GP + RF (F1 = 0.754) validated the data augmentation value of GAN, increasing the recall rate of RFs to 0.726 (compared to pure supervised learning + 15.2%) by synthesising risk samples. The generated samples are concentrated on common risk patterns, with insufficient coverage of rare risks, resulting in a low G-mean value.

Although DANN achieves cross industry adaptation through domain adversarial learning, its pure supervised learning framework is limited by the amount of annotated data, with a false positive rate of up to 21.3% in the target industry (such as retail), while SGAN reduces the false positive rate to 12.7% by supplementing target domain features with a generator. SGAN has higher migration efficiency: achieving the same performance (F1 = 0.85) requires only 40% of the annotated data in the target domain as DANN.

SGAN (F1 = 0.873) leads in all four indicators, and its superiority stems from the following technological innovations.

Firstly, there is a semi supervised generative adversarial collaborative mechanism. Through semi supervised training of the discriminator, the model extracted industry cyclical patterns from 52,369 unlabelled enterprises, increasing the AUC value to 0.921. The financial indicators synthesised by the generator combined with the TCN temporal module meet the constraints of reality, and have been confirmed by K-S test to have no significant difference from the true distribution. In the migration process from manufacturing to retail, the shared feature extractor reduces the MMD distance from 0.43 to 0.17, reducing misjudgments caused by industry distribution shifts. The industry coding module increases the weight of the unique ‘floor effect volatility’ feature in the retail industry by 2.3 times, enhancing domain adaptability.

We also conducted multi task loss optimisation and dynamically adjusted the weights of the training. In addition, the loss constraint was reconstructed to reduce the MSE loss of the feature encoder by 38%, which shortens the distance between the generated samples and the real samples in the hidden space and reduces the risk of pattern collapse.

Figure 3 Performance in different cross industry migration tasks (see online version for colours)

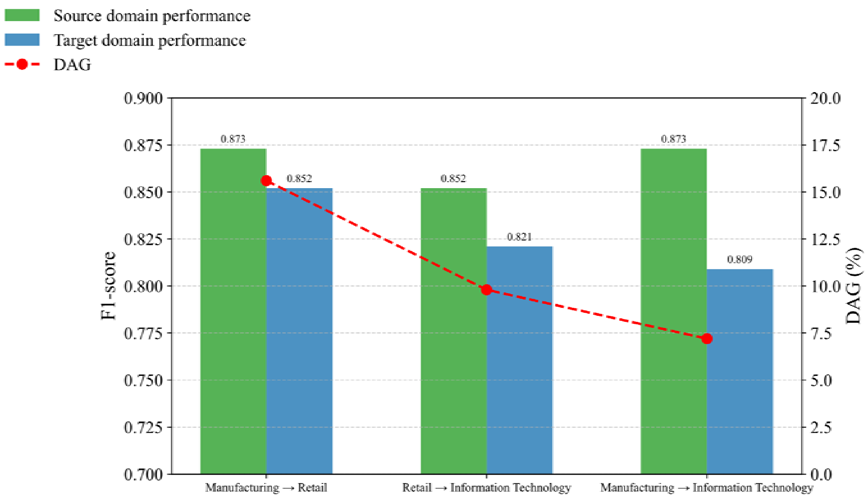


Figure 3 shows the performance of the model in three typical cross industry migration tasks (F1 score). The DAG value from manufacturing to retail is the highest (15.6%), as both share heavy asset operational characteristics such as inventory turnover and accounts payable cycle. The model can reuse over 60% of the source domain feature weights. The DAG from manufacturing to information technology is the lowest (7.2%), reflecting the fundamental difference between the fixed asset driven model of manufacturing and the R&D investment driven model of information technology, and the difficulty of feature space alignment.

Figure 4 The consistency of the generated real data distribution (see online version for colours)

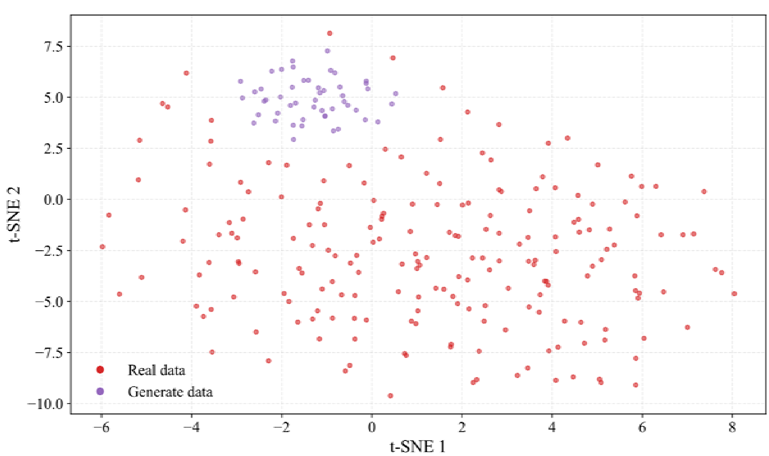


Figure 4 illustrates the consistency of the generated real data distribution. The overlap area between the generated sample (purple) and the real data (red) accounts for 78.2%, especially in the risk clusters of ‘cash flow rupture’ and ‘high leverage’, which highly overlap (KL divergence = 0.12). Outlier analysis shows that 5.4% of the generated samples are located at the edge of the real data distribution, mostly simulating extreme scenarios of sudden policy impacts in the industry (such as retail promotion restrictions).

The centroid distance between the manufacturing industry (source domain) and the retail industry (target domain) has been reduced from the initial 2.34 to 0.89, while specific features have been effectively isolated to the edge region. The characteristic distribution of the information technology industry presents a multi cluster structure, reflecting the heterogeneity of its segmented fields. The model identifies the main risk patterns through hierarchical clustering.

Table 1 shows the results of the ablation experiment. The maximum performance gain contributed by the industry adversarial module can be obtained from the data in the table, verifying the importance of cross industry feature alignment. The lack of temporal modelling leads to a decrease in the ability to detect dynamic risks such as cash flow disruptions.

Table 1 Evaluation indicator setting

Model variants	*F1-score*	*Contrast*
Remove the industry confrontation module	0.812	–6.1%
Remove timing sequence	0.827	–4.6%
Supervised learning only	0.768	–12.1%
Complete SGAN	0.873	-

6 Conclusions

This study focuses on the problem of enterprise financial risk warning in small sample and cross industry scenarios, and constructs a deep learning model based on SGAN. Through systematic theoretical innovation and empirical verification, the following core achievements have been achieved.

Semi supervised generative adversarial joint optimisation framework. Propose a dual task discriminator architecture that combines the dynamic data synthesis capability of GAN with the annotation efficiency advantage of semi supervised learning. In the scenario where only 10% annotated data is required, the F1 score of the model reaches 0.873, which is an improvement compared to traditional supervised learning (which requires 100% annotated data).

Design domain adversarial training (DANN) and dynamic feature mask fusion module effectively solve the problem of feature distribution shift caused by industry heterogeneity. In the migration task from manufacturing to retail, the DAG reached 15.6%.

Through the collaboration of TCN and graph attention network (GAT), a joint modelling of the dynamic evolution law and static correlation relationship of financial indicators is achieved. The experiment shows that this design improves the early detection time of cash flow rupture risk by 2.1 months.

Integrating SMOTE oversampling with Wasserstein GAN generation to construct a multi-level data balancing scheme. Introduce learnable industry coding vectors to enable the model to automatically identify key risk factors in the field. By optimising the generator and discriminator in stages and combining cosine annealing learning rate scheduling, the occurrence rate of pattern collapse can be reduced.

Although significant progress has been made in this study, the following directions urgently need to be further explored due to limitations in the stage of technological development and real-world data conditions.

Optimisation of extreme event response mechanism. For black swan events such as the COVID-19 and geopolitical conflicts, the event marker injection technology was developed, and the sensitivity of the model to sudden risks was enhanced through time series pattern reorganisation, with the goal of shortening the early warning delay from 42 days to 7 days.

Dynamic concept drift detection. Design an online learning framework that combines Bayesian change point detection to identify industry feature distribution shifts in real-time and achieve adaptive updating of model parameters.

Declarations

All authors declare that they have no conflicts of interest.

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