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Optimization Path of AI Technology Empowering Financial Market Risk Management in the Digital Transformation Environment

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SUMMARY: *In the context of digital transformation, in order to explore the optimization path of AI technology empowering financial market risk management, solve the problems of improving accuracy and model interpretability of machine learning in stock price prediction, and achieve better financial market risk control. This article proposes a Full-Scale Channel Simple Graph Convolutional Transformer Prediction Model (FSC-SGC Transformer), which combines SGCT blocks with the advantages of SGC and Transformer to mine channel relationships; Realize multi-scale feature fusion through Lightweight Channel Cross Fusion; Utilize channel cross attention to fuse inconsistent features. Construct a multi-objective portfolio optimization model (M-SV-S), considering factors such as transaction costs, and solve it using differential evolution algorithm. The experiment uses a "rolling window" to simulate investment, calculates indicators such as cumulative return rate and annual Sharpe ratio, and compares them with the proportional model and Shanghai Securities Composite Index. The results show that under different transaction costs and upper bound constraints, the cumulative rate of return of the proposed model is significantly higher than that of the comparative model, and the overall level of annual Sharpe ratio is higher. On the research surface, the proposed model performs better in financial market risk management, effectively improving investment returns and reducing risks.*

KEYWORDS: *digital transformation; AI technology; Financial market risk management; Transformer model; Portfolio optimization; Rolling window simulation investment*

1 Introduction

Pre selecting high-quality stocks in the stock market as a stock pool for financial market risk management is a key step in formulating the optimal financial market risk management strategy, and also a key factor in empowering financial market risk management with AI technology in the digital transformation environment [1, 2]. Due to the fact that the stock market is essentially a dynamic, constantly evolving, and nonlinear system, machine learning models demonstrate stronger advantages compared to traditional econometric models when dealing with its nonlinear and non-stationary features, enabling better risk management in financial markets.

The application of machine learning models in stock prediction and financial market risk management has received widespread attention from scholars both domestically and internationally. Research has shown that investment strategies constructed based on machine learning models can achieve better investment performance than traditional linear algorithms. Generate time series data based on text mining techniques and sentiment analysis methods, and use support vector machines and neural networks to predict changes in stock market prices [3].

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We used the Extreme Gradient Boosting algorithm (XGBoost) and other machine learning algorithms to study the rise and fall of constituent stocks of the CSI 300 and CSI 500 indices. The application of deep learning has been studied in the prediction of returns and factor investment in the Chinese stock market. The research shows that deep learning has greatly improved the accuracy of return prediction and factor investment performance compared to linear models [4]. A index prediction model based on financial text sentiment analysis was proposed, and the rise and fall of the benchmark index (CSI300) were predicted. We used machine learning and traditional econometric models (neural network algorithm, K-nearest neighbor algorithm, and smooth transition autoregression model) to predict the buying and selling points of five European ETF indices [5]. Using Long Short Term Memory (LSTM) networks to process text data yields the best prediction results in both classification and regression tasks. At present, machine learning has been preliminarily applied in stock price prediction, but how to improve prediction accuracy is still a problem that needs to be explored. Based on existing research, the setting of machine learning hyperparameters has a fundamental impact on stock prediction accuracy [6]. Even if researchers know the role of each machine learning hyperparameter, it is difficult to accurately adjust them to obtain the optimal model. Therefore, it is crucial to adopt appropriate optimization methods to select the optimal machine learning hyperparameters. In recent years, metaheuristic algorithms have been used to optimize machine learning hyperparameters. Among them, the standard Firefly Algorithm (FA) is considered a useful tool for solving machine learning hyperparameter optimization problems due to its few parameters, simple operation, and strong robustness. However, standard FA has the problem of quickly getting stuck in local optima when solving complex optimization problems, so many scholars have made improvements based on standard FA. As [7] developed an improved FA to optimize the machine learning hyperparameters of Support Vector Regression (SVR), and introduced adversarial chaos strategy and dynamic adjustment strategy. Adopting improved FA to obtain the optimal machine learning hyperparameters for XGBoost model, thereby improving its prediction performance [8].

Although machine learning has shown great potential in stock price prediction and financial market risk management, the complexity of hyperparameter adjustment and the lack of model interpretability remain key issues that urgently need to be addressed. Although existing research has made some progress in improving model performance, it has not yet fully addressed the constraints of hyperparameter optimization and model transparency on practical application effectiveness. To this end, this article proposes the Full Scale Channel Simple Graph Convolutional Transformer (FSC-SGC Transformer) prediction model, which integrates the advantages of graph convolutional networks and Transformer architecture to capture dynamic features of financial markets while improving model interpretability. Further construct a multi-objective portfolio optimization model (M-SV-S), combined with differential evolution algorithm to achieve hyperparameter adaptive optimization, effectively balancing returns and risks. The experimental results show that the model is significantly better than the traditional benchmark model under different transaction costs and constraints, verifying its feasibility and superiority in empowering financial market risk management in the context of digital transformation, and providing a new theoretical framework and practical path for subsequent research.

2 Related research

In terms of financial market risk management theory, Markowitz proposed the Mean Variance Model (MV model) in the classic financial market risk management theory, which has overly strict assumptions and cannot better meet the ever-changing investment market. Therefore, many scholars hope to optimize and explore the model based on the Mean Variance Model by improving the model, selecting indicators, or searching directions. Among them, many influential models emerged, such as Markowitz's attempt in 1959 to replace variance with semi variance as the underlying risk measure in his original model, proposing the mean semi variance model [9, 10]. In 1994, J.P. Morgan, an investment bank, pioneered the measurement of financial risk by proposing a new measurement method based on the potential loss of investments in the RiskMetrics system - Value at Risk (VaR) method, which summarizes and quantifies financial market risk losses using a simple number. It has become one of the most important tools in measuring financial market risk losses. Regarding option pricing theory, in 1973, Merton creatively applied the Black Scholes Merton option pricing theory in practice, first using this option pricing theory in the measurement of credit risk, and thus setting a precedent for comprehensive application [11]. In 1999, Delianedis and Geskel further discussed the issue of default rate based on the KMV model. Research has shown that this model can effectively reflect credit risk issues and is sensitive to changes in risk. In 1923, Keynes was the first to explain what hedging theory is from an economic perspective. It was not until 1960 that Johnson first proposed using Markowitz's portfolio investment theory to modify and propose the minimum variance hedging theory. By managing the financial market risks of assets in two different markets, hedging is actually a new approach to financial market risk control. Through such financial market risk control, expected returns and the variance of expected returns can be well obtained, thereby determining trading positions in both markets and emphasizing effective risk management [12]. In 2011, James Albrecht proposed a new perspective on multivariate hedging model, which improved the theory of multivariate hedging based on "futures spot", introduced two risk measurement methods, VaR and CVaR, and proposed an optimal analysis method for multivariate futures hedging problems. In 2006, Harris and Shen established a futures hedging model based on the minimum VaR model and improved it. In the article, the author conducted sufficient research and proved these two different hedging ratios, and concluded through practical examples that the value of the minimum variance hedging ratio is higher than that of the minimum futures hedging ratio [13]. At the same time, the superiority of minimum futures hedging in practical applications was demonstrated.

Domestically, there is relatively little research on using GARCH to measure the risk of hedging portfolios. From 2008 to 2009, Chi Guotai, Yu Fangping, Wu Zhongran, Xu Qiang, and others explored the principles of hedging by incorporating VaR into the optimization process and calculated the optimal hedging ratio. They also analyzed the properties of the optimal hedging ratio based on VaR [14]. In the measurement and management methods of credit risk, Cheng Peng, Wu Chongfeng, and Li Weibing conducted a series of theoretical discussions and explorations, and analyzed the advantages, disadvantages, and characteristics of each part of the theory. Regarding the KMV model, Lu Wei et al. and Zhang Ling et al. further explored the functional relationship of the model and found that a credit risk assessment system is also needed for Chinese listed companies. Due to the significant differences in financial market environments between China and foreign countries, the model may not be entirely applicable. However, Lu et al. explored the conclusion that this option theory is still applicable in China's investment market through the good application of option theory, which has great practical significance in academic research. Cao Daosheng and He Mingsheng started from the perspective of commercial banks, comparing commonly used modern risk measures such as CVaR and VaR, and conducting comparative analysis based on the actual situation of China's financial market. They found that these measures are still applicable in China's financial market [15]. Zhai Dongsheng, Zhang Juan, and Cao Yunfa tested the KMV model by using 30 listed companies in China as examples, and found that the application of this model can still estimate the value and structure of Chinese enterprises well in the Chinese market. Yang Zhaojun, Li Zhi and others brought transaction costs into the financial market in 1999, and established a risk management and control model with transaction costs. For this model, their numerical solution is also proposed in the article, and some conditions for solving the model are discussed. In 2004, Luo Qiulan et al. introduced transaction costs and good assets into the model to obtain a new revised model, and priced investors' asset assets. In the spring of 2007, Liu Sanyang and A Chunxiang introduced non concave and non convex transaction cost functions into the exploration of risk management in financial markets, further exploring the model of relevant opportunities under typical transaction costs, overcoming the shortcomings of using covariance or variance as risk measurement indicators in traditional models, and providing evidence [16].

3 Problem description

In recent years, deep learning based models have achieved outstanding results in many sequence modeling tasks. However, the "black box" nature of deep learning models limits their application in financial decision-making and makes it difficult to win the trust of investors. In the field of financial decision-making, the interpretability of models is crucial for risk management, decision scrutiny, and user trust [17]. When faced with the high complexity, dynamic evolution characteristics, and widespread nonlinear interactions of financial markets, such simple linear models often exhibit inherent limitations in fully capturing market dynamics and achieving efficient decision-making capabilities. On the other hand, deep learning models, with their powerful non-linear fitting ability, can more effectively cope with these complexities and improve decision performance, but their "black box" nature brings challenges to understanding and trusting their decision logic [18].

3.1 Financial Market Risk Management Based on Deep Learning

Figure 1 outlines a classic financial market risk management decision-making framework based on deep learning, which takes the historical state of assets as input and constructs a three-dimensional state tensor reflecting the current market situation. The state tensor is extracted and transformed through a neural network model, and finally outputs an asset rating vector as a reference for risk management decisions in different asset financial markets [19].

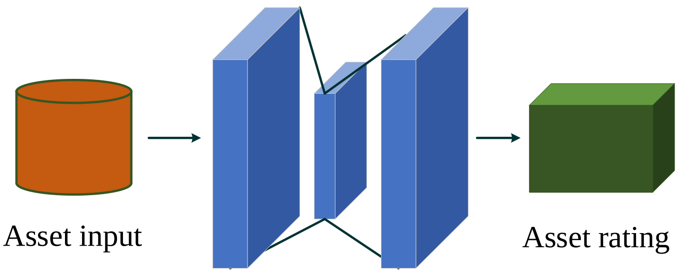


Figure 1: End to end financial market risk management decisions based on deep learning

The asset input is usually a real-time three-dimensional market environment state tensor $\mathcal{X}_t = \left(\boldsymbol{X}_{t,1}, \boldsymbol{X}_{t,2}, \cdots, \boldsymbol{X}_{t,m}\right) \in \mathbb{R}^{m \times W \times f}$, which comprehensively describes the state of all assets in the current market. The tensor is composed of the recent state matrix $\boldsymbol{X}_{t,i} = \left(\boldsymbol{x}_{t-W+1,i}, \boldsymbol{x}_{t-W+2,i}, \cdots, \boldsymbol{x}_{t,i}\right) \in \mathbb{R}^{W \times f}$ of each asset, reflecting the recent performance of the asset.

Each state matrix contains W historical states $\boldsymbol{x}_{t,i} = \left(x_{t,i}^1, x_{t,i}^2, \cdots, x_{t,i}^f\right) \in \mathbb{R}^f$ from transaction $t - W + 1$ to *t*, fully capturing all feature dimensions of the asset in each period.

It is crucial to standardize the time series data of various assets in order to improve the training effectiveness of the model. For each asset *i*, the following standardized transformation is adopted [20, 21]:

$$z_{t,i}^j = \frac{x_{t,i}^j - \mu_i^j}{\sigma_i^j} \tag{1}$$

where, μ_i^j and σ_i^j respectively represent the mean and standard deviation of feature *j* in the past time window *W*. This standardization process effectively eliminates the impact of differences in feature dimensions and enhances the numerical stability of the model. After standardization, the standardized market environment state tensor $\mathcal{Z}_t = \left(\boldsymbol{Z}_{t,1}, \boldsymbol{Z}_{t,2}, \cdots, \boldsymbol{Z}_{t,m}\right) \in \mathbb{R}^{m \times W \times f}$ is obtained as the input of the model. This processing method not only prevents certain features from being excessively affected by large dimensions on the model, but also effectively reduces the differences in data distribution of different asset states, laying a good foundation for subsequent model training.

For the decision-making problem of risk management in financial markets, three main neural network structures are usually considered: recursive neural networks (RNN, LSTM, etc.), convolutional neural networks (CNN, TCN, etc.), and Transformers [22]. Recurrent neural networks overcome the limitations of traditional feedforward neural networks in processing sequence inputs by introducing neurons with self feedback, making the network output not only related to the current input, but also closely related to the output of the previous moment, thus introducing the concept of time dimension to the model. Long short-term memory networks, as an extension of recurrent neural networks, effectively alleviate the problem of gradient vanishing through carefully designed gating mechanisms. Although these models have relatively simplified parameters and fast training speed, they have certain limitations in capturing long-term temporal dependencies. Convolutional neural networks (CNNs) effectively extract local feature information through convolutional kernels, and parameter sharing mechanisms significantly improve computational efficiency, although their performance in global information extraction is not ideal [23, 24]. Temporal Convolutional Networks (TCNs) have achieved good results in temporal modeling by introducing residual connections and gating mechanisms. Transformer, with its innovative self-attention mechanism, can efficiently model global dependencies. Although its computational complexity is high, parallel computing can significantly accelerate the processing process and demonstrate excellent performance in long sequence modeling.

3.2 Multi Objective Financial Market Risk Management Model

Assuming that investors invest their initial wealth W_0 in one risk-free asset and $n(n \in \mathbb{N}_+)$ risky assets. Let x_i represent the investment proportion of risk asset *i*; $\boldsymbol{X} = \left(x_1, x_2, \cdots, x_n\right)$ represents the investment portfolio; x_i^0 represents the initial investment proportion of risk asset *i*, and $x_i^0 = 0 (i = 1, 2, \cdots, n)$; r_i representing the random rate of return of risk asset *i*; $\hat{r}_i$ represents the predicted value of the rate of return r_i; $\hat{\sigma}_{ij}^-$ represents the predicted value of the lower covariance of r and r_j; $\hat{\boldsymbol{\Sigma}}^-$ representing the predicted values of the lower covariance matrix representing *n* risk assets; r_{N} represents the net return on investment portfolio *X*; l_i, u_i representing the lower and upper bounds of x_i respectively, where $u_i \geq l_i \geq 0$; $c_i \geq 0$

represents the unit transaction cost of the *i*-th risk asset; $r_{\mathrm{f}} \geq 0$ represents the risk-free asset return rate; $x_{\mathrm{f}}^{\mathrm{b}} \leq 0$ represents the maximum lending limit for risk-free assets.

The net return of an investment portfolio can be expressed as:

$$r_{\mathrm{N}} = \sum_{i=1}^{n} \hat{r}_i x_i - \sum_{i=1}^{n} c_i \left| x_i - x_i^0 \right| + \left(1 - \sum_{i=1}^{n} x_i \right) r_{\mathrm{f}} \tag{2}$$

The lower half variance of an investment portfolio can be expressed as:

$$\mathrm{SV} = \mathbf{X}^{\mathrm{T}} \hat{\mathbf{\Sigma}}^{-} \mathbf{X} = \sum_{i=1}^{n} \sum_{j=1}^{n} \hat{\sigma}_{ij}^{-} x_i x_j \tag{3}$$

where, $\hat{\mathbf{\Sigma}}^{-} = \left[\hat{\sigma}_{ij}^{-} \right]_{n \times n}$, $\hat{\sigma}_{ij}^{-} = E\left[\left(r_i - \hat{r}_i \right)^{-} \left(r_j - \hat{r}_j \right)^{-} \right]$, $\left(r_i - \hat{r}_i \right)^{-} = \min\left\{ r_i - \hat{r}, 0 \right\}$.

The skewness of an investment portfolio can be expressed as:

$$S = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{q=1}^{n} \hat{s}_{ijq} x_i x_j x_q \tag{4}$$

where, $\hat{s}_{ijq} = E\left[\left(r_i - \hat{r}_i \right) \left(r_j - \hat{r}_j \right) \left(r_q - \hat{r}_q \right) \right]$ is the predicted value of the co skewness of r_i, r_j, r_q.

Considering transaction costs, borrowing and lending constraints, and upper and lower bound constraints, construct a multi-objective portfolio optimization model (M-SV-S) with mean, lower semi variance, and skewness:

$$f_1 = \max \sum_{i=1}^{n} \hat{r}_i x_i - \sum_{i=1}^{n} c_i \left| x_i - x_i^0 \right| + \left(1 - \sum_{i=1}^{n} x_i \right) r_{\mathrm{f}} \tag{5}$$

$$f_2 = \min \sum_{i=1}^{n} \sum_{j=1}^{n} \hat{\sigma}_{ij}^{-} x_i x_j \tag{6}$$

$$f_3 = \max \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{q=1}^{n} \hat{s}_{ijq} x_i x_j x_q \tag{7}$$

$$\text{s.t.} \begin{cases} 1 - \sum_{i=1}^{n} x_i \geq x_{\mathrm{f}}^{\mathrm{b}} \\ l_i \leq x_i \leq u_i \quad (i = 1, 2, \cdots, n) \\ x_i \geq 0 \quad (i = 1, 2, \cdots, n) \end{cases} \tag{8}$$

where, the first optimization objective is to maximize the net return of the investment portfolio, the second optimization objective is to minimize the downside risk of the investment portfolio, and the third optimization objective is to maximize the skewness of the investment portfolio; The first constraint represents lending constraints, the second constraint represents upper and lower bounds on the investment ratio of each risk asset, and the third constraint represents short selling restrictions.

The solution of the M-SV-S model actually involves two steps [25, 26]: first, convert the M-SV-S model into a single objective optimization model; Then, use differential evolution algorithm to solve the single objective optimization model. Due to the dimensional differences between the three optimization objectives of expected net return, lower half variance, and skewness in the M-SV-S model, this paper uses the maximum minimum normalization method to dimensionless the three objectives when converting them into a single objective investment portfolio model. Before applying the maximum minimum normalization method, the maximum and minimum values of the expected net return, lower half variance, and skewness of the demand solution are as follows:

(1) The investment portfolio model that maximizes the expected net return is [27]:

$$f_4 = \max \sum_{i=1}^{n} \hat{r}_i x_i - \sum_{i=1}^{n} c_i \left| x_i - x_i^0 \right| + \left(1 - \sum_{i=1}^{n} x_i \right) r_{\mathrm{f}} \tag{9}$$

$$\text{s.t.} \begin{cases} 1 - \sum_{i=1}^{n} x_i \ge x_{\mathrm{f}}^{\mathrm{b}} \\ l_i \le x_i \le u_i \quad (i = 1, 2, \cdots, n) \\ x_i \ge 0 \quad (i = 1, 2, \cdots, n) \end{cases} \tag{10}$$

The objective function value for model (9-10) to obtain the optimal solution is the maximum expected net return rate $r_{\max}$. Due to the fact that the investment object of this model includes risk-free assets, the minimum expected return rate $r_{\min}$ is the risk-free interest rate.

(2) Let the maximum and minimum values of the lower half variance of the investment portfolio be $\mathrm{SV}_{\max}$ and $\mathrm{SV}_{\min}$, respectively. According to the efficient investment frontier: $\mathrm{SV}_{\max}$ is the lower half variance when the net return of the investment portfolio is $r_{\max}$, and $\mathrm{SV}_{\min}$ is the lower half variance when the net return of the investment portfolio is $r_{\min}$.

(3) The investment portfolio model that maximizes skewness is [28]:

$$f_5 = \max \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{q=1}^{n} \hat{s}_{ijk} x_i x_j x_q \tag{11}$$

$$\text{s.t.} \begin{cases} 1 - \sum_{i=1}^{n} x_i \ge x_{\mathrm{f}}^{\mathrm{b}} \\ l_i \le x_i \le u_i \quad (i = 1, 2, \cdots, n) \\ x_i \ge 0 \quad (i = 1, 2, \cdots, n) \end{cases} \tag{12}$$

The objective function value for model (11-12) to obtain the optimal solution is the maximum value of portfolio skewness $S_{\max}$.

The investment portfolio model that minimizes skewness is [29]:

$$f_6 = \min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{q=1}^{n} \hat{s}_{ijk} x_i x_j x_q \tag{13}$$

$$\text{s.t.} \begin{cases} 1 - \sum_{i=1}^{n} x_i \ge x_{\mathrm{f}}^{\mathrm{b}} \\ l_i \le x_i \le u_i \quad (i = 1, 2, \cdots, n) \\ x_i \ge 0 \quad (i = 1, 2, \cdots, n) \end{cases} \tag{14}$$

The objective function value for model (13-14) to obtain the optimal solution is the minimum value of portfolio skewness $S_{\min}$.

4 FSC-SGC Transformer model

The SGCTNet proposed in this experiment combines the advantages of full-scale channels, GCN, and Transformer in extracting topological spatial information of financial market risk control and deep dependency relationships based on node financial market risk control features, thus fully exploring and utilizing the complex relationships between financial market risk control channels.

4.1 SGCT Model

The main structure of SGCTNet is SGCT blocks, which are specific functional components used to explore channel information. Figure 2 shows the design of the SGCT block, which is divided into two parts: SGC and Transformer. Each layer of GCNs captures information in the graph structure by aggregating the features of adjacent nodes, making it widely used in tasks that require processing spatial information. SGC further simplifies the network structure and improves its practicality by eliminating the activation function between multiple layers of GCNs.

The feature matrix Xe RCxB is used to represent the data of nodes. A single-layer GCN can be represented as:

$$\boldsymbol{H}^{l+1}=\sigma\left(\hat{\boldsymbol{D}}^{-\frac{1}{2}}\hat{\boldsymbol{A}}^{-\frac{1}{2}}\boldsymbol{H}^{l}\boldsymbol{W}^{l}\right) \tag{15}$$

where, $\boldsymbol{H}$ is the input and output feature matrix of each convolutional neural network layer. When $l=0$, $\boldsymbol{H}=\boldsymbol{X}$, $\hat{\boldsymbol{A}}$ is an adjacency matrix with self-loops and satisfies $\hat{\boldsymbol{A}}=\boldsymbol{A}+\boldsymbol{I}$, and $\hat{\boldsymbol{D}}$ is the degree matrix corresponding to $\hat{\boldsymbol{A}}$. $\hat{\boldsymbol{D}}^{-1/2}\hat{\boldsymbol{A}}^{-1/2}$ is the normalization of $\hat{\boldsymbol{A}}$. $\boldsymbol{W}^{l}$ is the weight matrix of the first layer, $\boldsymbol{W}^{l}\in\mathbb{R}^{d,d'}$ is the parameter that needs to be updated during network training, and the dimension of the feature matrix $\boldsymbol{H}$ can be changed through the linear transformation of $\boldsymbol{W}^{l}$. σ is an activation function.

SGC removes the activation function in the middle of multiple GCN layers, and its simplified formula can be expressed as:

$$\boldsymbol{H}^{L+1}=\sigma\left(\boldsymbol{S}\boldsymbol{H}^{L}\boldsymbol{W}^{L}\right)=\cdots=\sigma\left(\boldsymbol{S}^{L}\boldsymbol{X}\boldsymbol{W}\right) \tag{16}$$

where, $\boldsymbol{H}^{L+1}$ is the feature representation output by multi-layer GCNs, $\boldsymbol{S}=\hat{\boldsymbol{D}}^{-1/2}\hat{\boldsymbol{A}}^{-1/2}\hat{\boldsymbol{D}}^{-1/2}$, and $\boldsymbol{W}=\boldsymbol{W}^{0}\boldsymbol{W}^{1}\cdots\boldsymbol{W}^{L}$. This way, only one layer of $\boldsymbol{W}$ needs to be learned to complete the task, reducing the number of model parameters and computational complexity. In addition, it is hoped that the self-attention mechanism of SGC and Transformer will be consistent and only include linear transformations, so the activation function has been removed, as shown in equation (17).

$$\boldsymbol{H}^{L+1}=\boldsymbol{S}^{L}\boldsymbol{X}\boldsymbol{W} \tag{17}$$

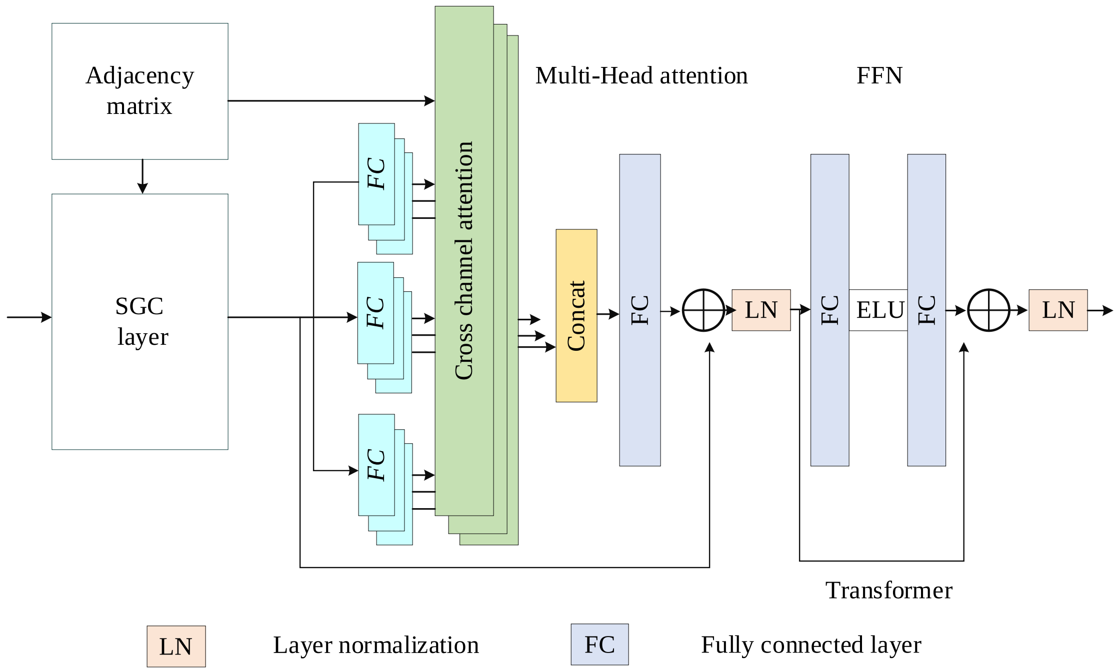


Figure 2: Architecture diagram of SGCT module

Through the above formula, it can be concluded that the adjacency matrix $\boldsymbol{A} \in \boldsymbol{R}^{C \times C}$ shown in Figure 2 is the key for SGC to extract topological information. It represents the weight between channel *i* and channel *j*, denoted as A_{ij}, and is less than or equal to 1. Like RGNN, the adjacency matrix is set to be learnable and symmetric, and physical distance is used to measure the relationship between channels *i* and *j*, as shown in equation (18).

$$\boldsymbol{A}_{ij} = \min\left(1, \frac{\delta}{d_{ij}^2}\right) \tag{18}$$

where, d_{ij} representing the physical distance between channels *i* and *j*, δ is a hyperparameter. Compared with the RGNN using δ =5, the model in this experiment achieved better results at δ =10. A larger δ means that the initial value in $\boldsymbol{A}$ is larger. It is worth noting that although random initialization of $\boldsymbol{A}$ is allowed, experiments have found that initializing the adjacency matrix with distance is more effective.

4.2 Lightweight Channel Cross Fusion

FCTrans changes the interconnection between the encoder and decoder through Transformer. It consists of two modules: the Light weight Channel wise Cross Fusion Transformer (LCCT) for multi-scale encoder feature fusion and the Channel wise Cross Attention (CCA) module for fusing LCCT output and decoder features. Both traditional ordinary connections and Transformer based UCTransNet lack sufficient information to explore at full scale and cannot clearly learn the location and boundaries of organs. Each decoding layer in FCTransNet combines smaller and same scale global contextual feature maps from the LCCT module and larger scale feature maps from the decoding layer through CCA, capturing fine-grained details and coarse-grained semantics at full scale.

Unlike traditional ViT, introducing Transformer to establish dependencies between different scales in the skip connection part requires a large number of self-attention operations on the channel axis, that is, the attention operation changes from matrix multiplication ($H \times W$, C) (C,

$H \times W$) to (C_Q, $H \times W$) ($H \times W$, C_k), where H, W, and C represent the height, width, and channel dimension of the feature map, and C represents the channel dimension of the token query, and C_k represents the channel dimension of the token key. In UCTransNet, the token representing the key is simply merged on the channel through four scale features, which makes the channel dimension of the key reach an astonishing 960. When the token representing the four queries performs self-attention operation with it, the maximum single operation computation reaches 512 × 960, and the model becomes bulky and cumbersome, reducing its universality. During the process of reconstructing the input four scale feature maps into sequences, the LCCT block uniformly reduces their channel numbers to 64, and the maximum single operation computation is only 64 × 256, which can significantly reduce the computational complexity. LCCT consists of three steps: light weight embedding, Transformer layers, and multi-scale reconstruction.

1) Lightweight embedding. In the network, the three-dimensional feature map tensor needs to be transformed into a two-dimensional tensor in order to serve as input for the Transformer layer. Specifically, the encoder outputs four feature maps F of different scales to the LCCT block: $\boldsymbol{F}_i \in \boldsymbol{R}^{\frac{H}{i} \times \frac{W}{i} \times c_i} (i = 1, 2, 3, 4)$, with channel numbers of C_1=64, C_1=128, C_1=256, and C_1=512. The input feature map is reduced to 64 channels through a 1 × 1 convolutional layer, and then tokenized to reconstruct these feature maps into a flat two-dimensional sequence of pixel blocks (patches), where the size of the pixel block patch is four tokens of the same scale $\boldsymbol{t}_i \in \boldsymbol{R}^{d \times 64} (i = 1, 2, 3, 4)$:

$$\boldsymbol{t}_i = \mathrm{Conv}_{1\times1}\left(\boldsymbol{F}_i\right)\boldsymbol{E}_i + \boldsymbol{E}_{\mathrm{pos}} \tag{19}$$

where, $\boldsymbol{E}_i \in \boldsymbol{R}^{\left(P_i^2 \times 64\right) \times 64}$ represents patch em embedding projection, and $\boldsymbol{E}_{\mathrm{pos}} \in \boldsymbol{R}^{d \times 64}$ represents position embedding.

2) Transformer layer. Each LCCT module uses a series of Transformer layers, including two sub layers: Multi head Cross Attention (MCA) and Multi Layer Perceptron (MLP). For the structure of LCCT one layer Transformer, the first $j (j = 2, 3, 4)$ tokens and the new token t obtained by fusing them on the channel axis $\boldsymbol{t}_j = Concat\left(t_1, t_2, \cdots, t_i\right)(i = j)$ is used as the query $\boldsymbol{Q}_j^i$ for the MCA layer through linear projection , key $\boldsymbol{K}_j$, and value $\boldsymbol{V}_j$:

$$\boldsymbol{Q}_j^i = \boldsymbol{W}_{Q_j}\boldsymbol{t}_i, \boldsymbol{K}_j = \boldsymbol{W}_{K_j}\boldsymbol{t}_j, \boldsymbol{V}_j = \boldsymbol{W}_{V_j}\boldsymbol{t}_j \tag{20}$$

where, $\boldsymbol{W}_{Q_j} \in \boldsymbol{R}^{d \times C}$, $\boldsymbol{W}_{K_j} \in \boldsymbol{R}^{d \times C_j}$ and $\boldsymbol{W}_{V_j} \in \boldsymbol{R}^{d \times C_j}$ is the learnable weight matrix.

Unlike traditional self-attention that performs attention operations along the patch axis, FCtrans performs attention operations along the channel axis. The MCA module of LCCT performs matrix multiplication with input keys after transpose of two-dimensional query tokens. After a series of operations, the attention weight $\boldsymbol{A}_j$ is obtained:

$$\boldsymbol{A}_j = \mathrm{Softmax}\left[\sigma\left(\frac{\boldsymbol{Q}_j^{i\,\mathrm{T}}\boldsymbol{K}_j}{\sqrt{C_j}}\right)\right] \tag{21}$$

where, $\boldsymbol{A}_j \in \boldsymbol{R}^{C \times C_j}$ represents the matrix size of attention weights, C_j is a scaling factor used to keep weights within a controllable range, and $\sigma(\cdot)$ is an instance normalization operation that makes gradient propagation smoother.

The attention weights are transposed with the token representing the value, and a matrix multiplication is performed again to restore the size of the two-dimensional pixel block, making it consistent with the input. The final output of the cross-attention operation can be expressed as:

$$\boldsymbol{C}_{A_j} = \xi\left(\boldsymbol{A}_j \boldsymbol{V}_j^{\mathrm{T}}\right) \tag{22}$$

where, ξ represents a generalized transpose, where $\boldsymbol{C}_{A_j} \in \boldsymbol{R}^{d \times C}$ maintains the same size as the input. In the case of N_j attention heads, the attention of multiple heads can be considered as an ensemble of the original attention layers.

Each attention head will receive a $\boldsymbol{C}_{A_j}$, and after merging and compressing these results in the channel dimension, the output of the multi head cross attention operation can be expressed as:

$$\boldsymbol{M}_{\mathrm{CA}_j} = \left(\boldsymbol{C}_{A_j^1} + \boldsymbol{C}_{A_j^2} + \cdots + \boldsymbol{C}_{A_j^{N_j}}\right) / N_j \tag{23}$$

where, N_j is the number of heads, and in LCCT, N_j is also the number of Trans form layers. Finally, the final output $\boldsymbol{O}_j$ is obtained through a simple MLP layer and residual operator:

$$\boldsymbol{O}_j = \mathrm{MLP}\left[L_{\mathrm{norm}}\left(\boldsymbol{M}_{\mathrm{CA}_j} + \boldsymbol{Q}_j^i\right)\right] + \boldsymbol{M}_{\mathrm{CA}_j} \tag{24}$$

where, L_{norm} represents layer normalization, while MLP consists of two linear layers with CELU activation functions.

3) Refactoring. The output $\boldsymbol{O}_j$ is expanded from a two-dimensional sequence to a three-dimensional feature map and restored to its original size through up sampling. The number of channels is restored to the number of inputs through a 1×1 convolution to match the number of channels in the decoder feature map.

4.3 Cross channel Attention

Similar to UCTransNet, CCA module is used to fuse inconsistent features between FCTrans and decoder. The feature maps from FCTrans and decoder are embedded into the global spatial information through a Global Average Pooling (GAP) layer, generating an attention mask $\boldsymbol{M}_j$:

$$\boldsymbol{M}_j = \left[\varphi\left(\boldsymbol{O}_j\right) + \varphi\left(\boldsymbol{D}_j\right)\right] / 2 \tag{25}$$

where, φ is a global average pooling operation. Using Sigmoid and ReLU functions to process the fused feature maps of attention masks $\boldsymbol{M}_j$ and $\boldsymbol{O}_j$:

$$\hat{\boldsymbol{O}}_j = \mathrm{ReLU}\left[\mathrm{Sigmoid}\left(\boldsymbol{M}_j\right)\boldsymbol{O}_j\right] \tag{26}$$

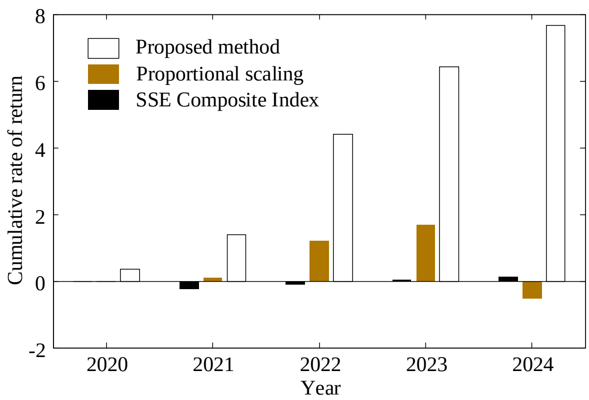
Finally, the obtained $\hat{\boldsymbol{O}}_j$ is merged with the upsampling feature map of the decoder.

5 Experimental analysis

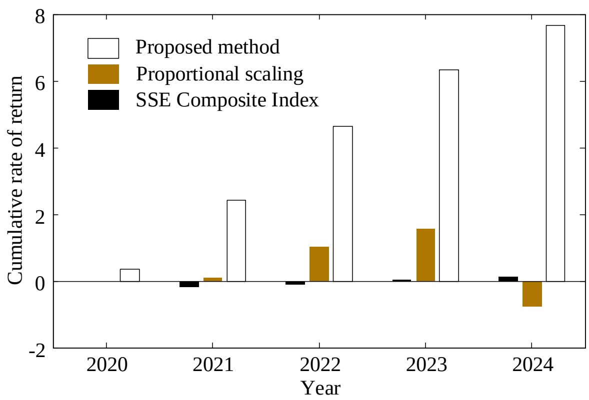
This article uses the "rolling window" approach to simulate investment. Calculate the cumulative return, annual Sharpe ratio, and annual Tito ratio of the Proposed method and the proportional model (1/N), and compare them with the Shanghai Securities Composite Index to test the effectiveness of the model. For a given T months of expected asset return data, select an estimation window with a length of M=60. Starting from t=M+1, use the data from the previous M months to estimate the parameters required for the model, solve for the optimal financial market risk control, and calculate the returns and risks of the optimal financial market risk control. After completing the calculation, add the next period's earnings to the original M month data window and delete the earliest period's earnings. Repeat the above process until t=T. The result of the above scrolling window is the financial market risk control weight x_j for the T-M period and the return R_j for each out of sample investment, where $j = 1, 2, \cdots, T - M$.

5.1 Cumulative rate of return

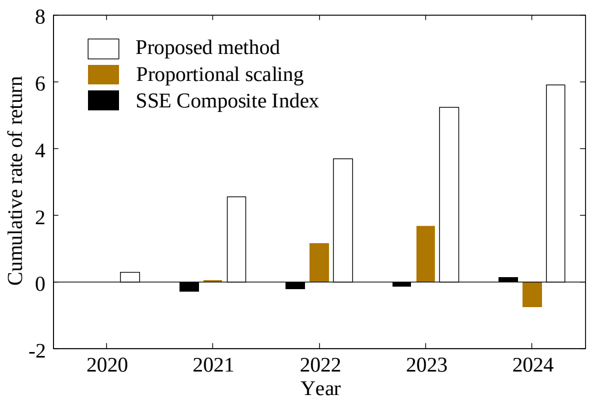
The cumulative rate of return in this article refers to the total rate of return obtained by investing in each model during the out of sample period, and accumulating the returns obtained in each period until the end of the out of sample period. This article compares the differences in cumulative returns between the Proposed Method model, the Proportional Model, and the Shanghai Securities Composite Index, and presents the investment results of the three models. It also analyzes the changes in cumulative returns when the upper bound of risk asset trading volume and trading costs change. The results are shown in Figure 3.



(a) c=0.001, u=0.3



(b) c=0.003, u=0.3



(c) c=0.003, u=0.3

Figure 3: Cumulative rate of return for each model under different parameter conditions

1) When the transaction cost c=0.001 and the upper bound constraint u=0.3, as shown in the figure, the cumulative return of the Proposed method model is significantly higher than that

of the proportional model and the Shanghai Securities Composite Index, and the upward trend is relatively stable. The research results show that the cumulative return of the Proposed method model reached 855.48%, while the cumulative returns of the proportional model and the Shanghai Securities Composite Index were -49.57% and -1.83%, respectively It is not difficult to see that the proposed method model considered in this article performs the best in comparing cumulative returns outside the sample.

2) When the transaction cost c=0.003 and the upper bound constraint u=0.3, compared to situation (1), the transaction cost per unit investment increases, and the cumulative returns of the Proposed method model and the proportional model both decrease. This is consistent with the conclusion drawn from the in sample test. At this time, due to the increase in investment cost, the cumulative return of the Proposed method model is 849.82%, slightly lower than situation (1), and the cumulative return of the proportional model is -61.39%, still significantly lower than that of the Proposed method model. Even with an increase in transaction costs, the proposed method model still has the highest cumulative rate of return.

3) When the transaction cost c=0.003 and the upper bound constraint u=0.1, it is not difficult to observe that as the upper bound constraint on the trading volume of risky assets decreases, the proportion of high-yield stocks that investors can invest in their assets decreases, resulting in a significant decrease in the cumulative return of the Proposed method model. Since the proportional model is not affected by this upper bound constraint, the cumulative return is the same as in case (2). At this point, the cumulative return of the Proposed method model decreased to 653.79%, but it was still significantly higher than the cumulative return of the proportional model and the Shanghai Securities Composite Index. The out of sample cumulative return performance of the Proposed method model remained the best. From the out of sample empirical results of cumulative returns, it can be seen that the cumulative investment return of the Proposed method model is significantly higher than that of the proportional model and the Shanghai Securities Composite Index in different situations. That is, using the Proposed method model for investment decisions during the out of sample period yields the highest cumulative return, and performs the best among the three models.

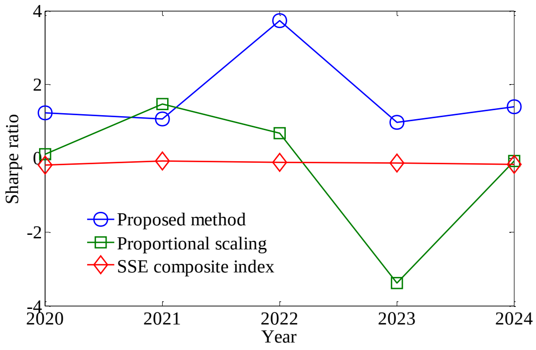
5.2 Comparison of Sharpe Ratio in Different Model Years

The Sharpe ratio, as an evaluation indicator, can simultaneously consider the benefits and risks of financial market risk management. The higher the Sharpe ratio, the higher the return obtained while assuming the same risk. This article uses the annual Sharpe ratio to test the effectiveness of the proposed method model, and its calculation formula is as follows:

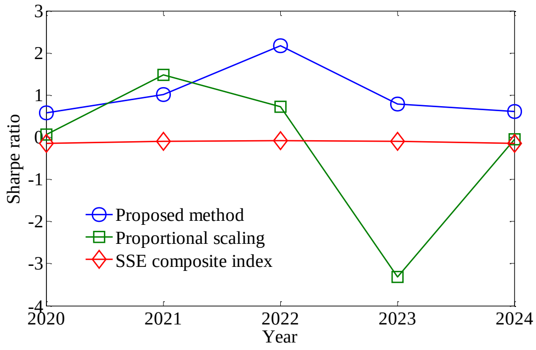
$$Sharpe = \frac{r_p - r_f}{\sigma_p} \tag{27}$$

where, r_p is the annualized rate of return for financial market risk management, r_f is the annualized risk-free rate, and σ_p is the standard deviation of the annualized rate of return for financial market risk management.

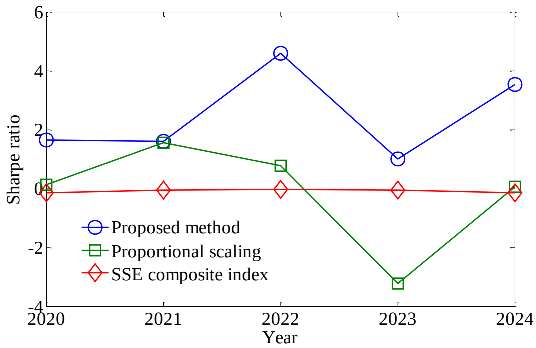
This article compares the annual Sharpe ratio of the Proposed method model, the proportional model, and the Shanghai Securities Composite Index from 2022 to 2024 when the upper bound of risk asset trading volume and trading costs change. The results are shown in Figure 4 and Table 1.



(a) c=0.003, u=0.3



(b) c=0.003, u=0.1



(c) c=0.001, u=0.3

Figure 4: Sharpe ratio of each model year under different parameter conditions

Table 1: Comparison of annual Sharpe ratios under different transaction costs and upper bound constraints

Parameter conditions (c, u)	Year	Proposed Method	Proportional Model
(0.003, 0.3)	2022	3.614	-3.209
(0.003, 0.3)	2023	2.850	-2.500
(0.003, 0.3)	2024	3.100	-2.800
(0.003, 0.1)	2022	2.053	-3.209
(0.003, 0.1)	2023	1.900	-2.500
(0.003, 0.1)	2024	2.100	-2.800
(0.001, 0.3)	2022	4.438	-1.500
(0.001, 0.3)	2023	4.000	-1.200
(0.001, 0.3)	2024	4.200	-1.300

1) When the transaction cost c=0.003 and the upper bound constraint u=0.3, it can be seen from the graph that from 2022 to 2024, the annual Sharpe ratio of the Proposed method model is greater than that of the Shanghai Securities Composite Index. Except for 2024, the annual Sharpe ratio of the Proposed method model is significantly higher than that of the proportional model in other years. Among them, the Sharpe ratio of the Proposed method model is greater than 1 in all years, with the highest Sharpe ratio in 2022 at 3.614, performing better among the three models; The Sharpe ratio of the proportional model fluctuates greatly, with unstable positive and negative values. When the Sharpe ratio is positive, the value is not high, and the lowest Sharpe ratio in 2023 is -3.209; The annual Sharpe ratio of the Shanghai Securities Composite Index fluctuates smoothly, with negative values close to zero.

2) When the transaction cost c=0.003 and the upper bound constraint u=0.1, the Sharpe ratio of the proportional model is the same as in case 1) because the investment is not limited by the upper bound constraint. However, the Proposed method model has shown a certain degree of decrease in the annual Sharpe ratio in each year. The annual Sharpe ratio in 2022 is still the highest, but compared to case 1), it has decreased to 2.053. This is because when the upper bound is lowered, the returns that can be obtained in the face of the same risk are smaller, that is, the Sharpe ratio will decrease. However, overall, the annual Sharpe ratio performance of the Proposed method model is still better than that of the proportional model and the Shanghai Securities Composite Index.

3) When the transaction cost c=0.001 and the upper bound constraint u=0.3, the decrease in transaction cost has a greater impact on the annual Sharpe ratio compared to situation 1). The annual Sharpe ratio of the Proposed method model has significantly increased, and the annual Sharpe ratio of the proportional model has also improved to a certain extent. The proposed method model has the highest Sharpe ratio in 2022, reaching 4.438. This is due to the reduction of transaction costs, which increases the returns that can be obtained from financial market risk control under the same risk, resulting in a larger Sharpe ratio. At this time, the annual Sharpe ratio of the Proposed method model is higher than that of the proportional model and the Shanghai Securities Composite Index in each year, and the Sharpe ratio of each year performs the best. From the empirical results of the annual Sharpe ratio, under various parameter conditions, the proposed method model considered in this article performs better than the proportional model and the Shanghai Securities Composite Index in the comparison of Sharpe ratios outside the sample. The overall level of the annual Sharpe ratio is higher. This is because after giving expected returns, the proposed method financial market risk management model aims to minimize risk and find the optimal investment strategy. Therefore, when comparing the Sharpe ratios of the three models, the overall performance of the Proposed method model will be better.

6 Conclusion

This article focuses on the core issue of AI technology empowering financial market risk management in the context of digital transformation, and systematically studies the optimization of stock price prediction models and multi-objective investment portfolio decision-making methods based on deep learning. The main work is reflected in the following three aspects: firstly, to address the problem of insufficient interpretability of traditional deep learning models, a full-scale channel simple graph convolutional Transformer (FSC-SGC Transformer) architecture is proposed. By integrating graph convolutional networks (SGC) and the self-attention mechanism of Transformers, explicit modeling of complex dependencies between channels is achieved while capturing the dynamic topology of financial markets; Secondly, to address the issue of information loss in multi-scale feature fusion, a lightweight channel cross fusion module (LCCT) was designed, which utilizes channel dimension compression and cross scale attention mechanism to enhance global feature extraction capability while maintaining model light weighting; Finally, a multi-objective portfolio optimization model (M-SV-S) was constructed, which includes maximizing returns, minimizing lower variance, and maximizing skewness. By combining differential evolution algorithm, hyperparameter adaptive optimization was achieved, effectively balancing the relationship between returns and risks in investment decisions. The experimental results show that the proposed model improves the cumulative rate of return by more than 700% compared to the proportional benchmark model under different transaction costs and constraints, and the annual Sharpe ratio increases by an average of 2.8 times, verifying its superiority and robustness in complex financial environments.

Although this article has made progress in model interpretability and multi-objective optimization, there are still several directions worth further exploration. Firstly, current research is mainly based on historical market data, and in the future, it can be combined with unstructured data such as news texts and social media to construct a multimodal financial market risk warning system; Secondly, the performance of existing models under extreme market conditions still needs to be validated, and adversarial training mechanisms can be introduced to enhance the adaptability of models in black swan events; Thirdly, with the development of quantum computing technology, the potential application of quantum neural networks in modeling ultra-high dimensional financial markets can be studied; Fourthly, there is a computational efficiency bottleneck in current optimization algorithms when dealing with large-scale asset portfolios, and more efficient distributed evolutionary algorithms need to be developed. Subsequent research will focus on these directions, continuously promoting the deep integration of AI technology and financial risk management, and providing theoretical support and technical guarantees for the construction of an intelligent financial market regulatory system.

About the Author

Yao Wang was born in China in 2000. Yao obtained a bachelor’s degree in International Trade in China and is currently completing postgraduate studies in Communication and Journalism at the University of New South Wales, Australia. Although Yao’s current academic training is in communication and journalism, this paper focuses on economic issues, drawing on Yao’s background in international trade.

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