

A Financial Enterprise Anomaly Detection and Interpretability Analysis Framework Combining Graph Attention Network and Self Supervised Pre Training

Ming Guo

Yunnan Normal University, Kunming 650000, Yunnan, China

Keywords: Graph attention network, self supervised pre training, multi-source data fusion, volatility prediction, interpretability analysis

Abstract: This study addresses the core challenge of predicting financial market volatility and innovatively constructs a financial enterprise anomaly detection and interpretability analysis framework based on graph attention network (GAT) and self supervised pre training. Through graph attention mechanism, it captures the node correlation and dynamic interaction of enterprises, and strengthens the weight of key information; Combining self supervised pre training with unlabeled data to learn universal feature representations and alleviate data sparsity issues; Integrating multi-source data fusion and attention mechanism optimization of volatility measurement methods (such as mean square of returns and its deviation square) to achieve comprehensive evaluation of prediction accuracy. Taking iShares China Large Cap ETF volatility as an example, the empirical verification framework outperforms traditional GARCH models and single deep learning models in capturing nonlinear patterns and handling long sequence dependencies; By visualizing attention weights and evaluating feature importance, interpretability analysis can be achieved to enhance decision credibility; The optimized volatility measurement method enhances the comprehensiveness of prediction accuracy testing and confirms the effectiveness and robustness of the model in complex financial environments. This study enriches the theory of financial time series analysis, proposes an innovative combination of graph structure learning and self supervised pre training, integrates multi-source data fusion, attention mechanism, and self supervised technology to construct an efficient anomaly detection model, and provides key support for the stable development and theoretical innovation of financial markets.

1. Introduction

The combination of Graph Attention Network (GAT) and self supervised pre training framework for anomaly detection and interpretability analysis of financial enterprises is an innovative direction to address the complexity of financial data and the limitations of traditional methods. As the core of the national economy, the volatility of the financial market is closely related to the rise and fall of the economy. However, traditional time series analysis is difficult to effectively handle the non stationarity, low signal-to-noise ratio characteristics, and complex nonlinear patterns of financial data due to the requirements of data normality and stationarity. Although deep learning has the ability of automatic feature extraction and nonlinear modeling, it still faces problems such as

overfitting, difficulty in parameter tuning, and insufficient handling of long sequence dependencies when applied directly. As a core indicator of market risk, accurate prediction of volatility is crucial for asset pricing and risk management. However, traditional methods such as GARCH models and stochastic volatility models are limited by strict assumptions (such as market efficiency and normal distribution) and nonlinear modeling capabilities, making it difficult to meet the needs of complex financial environments. This study focuses on the scenario of anomaly detection in financial enterprises, introducing graph attention networks to capture the correlation and dynamic interaction of enterprise nodes in the financial network, strengthening the weight of key information through attention mechanisms, and improving the accuracy of anomaly pattern recognition; By combining self supervised pre training techniques and utilizing unlabeled data to learn universal feature representations, the model's generalization ability is enhanced and the problem of data sparsity is alleviated. The framework design emphasizes interpretability analysis, revealing the decision-making logic of the model and enhancing the credibility and practical application value of the results through methods such as attention weight visualization and feature importance evaluation. Specifically, the framework integrates Gated Recurrent Unit (GRU) and Graph Attention Mechanism to construct a prediction model based on multi-source data fusion, breaking through the limitation of single data source information; Optimize volatility measurement methods (such as the mean square of returns and their squared deviations) to achieve a comprehensive evaluation of prediction accuracy. Through empirical testing (using iShares China Large Cap ETF volatility as an example), the superiority of the model in anomaly detection tasks is verified, and traditional methods are compared with existing deep learning models to highlight the advantages of the improved algorithm in nonlinear pattern capture, long sequence dependency processing, and interpretability. This study not only enriches the theory of financial time series analysis, but also proposes an innovative method combining graph structure learning and self supervised pre training to enhance the ability to capture nonlinear patterns and handle long-term dependencies; More innovatively integrate the graph attention network, self-monitoring pre training and multi-source data fusion technologies at the method level, build an efficient anomaly detection model, and solve the assumption limitations of traditional methods and the performance bottleneck of a single model. At the empirical level, the effectiveness of the model is verified through comparative experiments and actual case studies, and the volatility measurement method is optimized to improve the comprehensiveness of prediction accuracy testing, providing key support for the stable development and theoretical innovation of financial markets.

2. Correlation theory

2.1. Theoretical basis and classification of financial volatility

Financial volatility is a core indicator for risk assessment[1], asset pricing, and portfolio management in financial markets, reflecting the magnitude and frequency of price changes in financial assets and providing investors with objective risk measurement standards[2]. Its essence is to quantify the uncertainty of asset returns - measuring the degree to which prices deviate from the mean through standard deviation or variance[3]. High volatility corresponds to high market risk, while low volatility indicates relative stability. Volatility can be classified from multiple dimensions: by nature and data source[4], it can be divided into historical volatility (calculated based on past price data, reflecting actual changes) and implied volatility (inferred from option market prices[5], reflecting market expectations of future changes); According to the calculation method, it can be divided into simple volatility (estimated directly by standard deviation, ignoring time value) and weighted volatility (assigning weights to price changes at different time points to more accurately capture dynamic changes)[6]; According to application scenarios, it can be divided into actual

volatility (recording real volatility), predicted volatility (predicting future changes based on historical data), and model implied volatility (calculating expectations through financial models); By asset category[7], it covers the volatility of different assets such as stocks, bonds, commodities, and foreign exchange, each with unique risk attributes and patterns of change[8]. These classification dimensions provide investors and researchers with diverse risk measurement tools and decision-making basis[9], supporting financial practices such as asset pricing, risk management, and investment strategy optimization. They are an important cornerstone for analyzing financial market stability and theoretical innovation[10].

2.2. The Development and Parameter Setting of Volatility Models

The development of volatility models has gone through an evolution from simple to complex: historical volatility models are based on past asset price data calculations, which are simple but cannot reflect future changes; The implied volatility model is more comprehensive by extrapolating option market prices and incorporating market expectations of future changes; The random volatility model assumes that volatility itself is a stochastic process, which can more accurately capture the complexity and uncertainty of financial markets. Parameter setting needs to consider multiple factors comprehensively: the selection of time window directly affects the volatility calculation results and stability, and should be reasonably determined according to the application scenario and asset characteristics; The frequency and magnitude of price fluctuations directly determine the magnitude of volatility, with high-frequency fluctuations driving up volatility and vice versa; The microstructural factors of the market, such as trading mechanisms and participant behavior, cannot be ignored. For example, the market maker system may introduce additional noise and uncertainty, increasing the difficulty of calculating volatility. In practical applications, models and parameters need to be adjusted as needed - risk management focuses on accurately assessing risk levels, tends to choose complex models (such as implicit or random volatility models), and comprehensively sets parameters based on multiple factors; The formulation of trading strategies focuses more on the dynamic changes in volatility and the impact of market sentiment, and requires the use of flexible and sensitive models and parameter setting methods.

3. Research method

3.1. Theoretical basis and application of deep learning in financial time series analysis

Deep learning achieves powerful feature extraction and nonlinear modeling capabilities by constructing deep neural network models, demonstrating significant advantages in financial time series analysis. In traditional deep learning models, convolutional neural networks (CNNs) process grid structured data (such as images and speech) through convolutional layers, pooling layers, and fully connected layers. Convolutional kernels are used to capture local features, activation functions (such as ReLU) introduce nonlinearity, and pooling layers (such as maximum/average pooling) reduce dimensionality while preserving key information; Recurrent neural networks (RNNs) take sequence data as input and capture temporal dynamic changes through chain connected recurrent units. However, they face the problem of gradient vanishing/exploding. Long short-term memory networks (LSTMs) and gated recurrent units (GRUs) optimize long sequence dependency processing capabilities through gating mechanisms. In time series analysis, deep learning can be applied for prediction (such as stock prices, weather data), anomaly detection (such as autoencoder recognition of outliers), and classification (such as electrocardiogram, speech signal classification). Traditional financial time series models are divided into deterministic models (fitting to determine trends) and stochastic models (such as ARMA, ARIMA, ARCH, GARCH). ARIMA processes non-

stationary sequences through differencing, while GARCH extends ARCH models to capture long-term autocorrelation of volatility. Combining the advantages of deep learning and traditional fusion modeling methods such as ARIMA-LSTM and ANN-SVM-GARCH can improve prediction accuracy and interpretability; The Transformer model based on self attention mechanism breaks through the time step limitation of RNN and achieves global information parallel processing and long-term dependency capture, becoming a cutting-edge tool for time series analysis. Supervised learning (such as BP networks, CNN, RNN) and unsupervised learning (such as GAN, autoencoder) support complex analysis and decision optimization of financial time series through labeled data training and automatic pattern discovery, respectively.

3.2. Principle of Attention Mechanism

The attention mechanism originates from the selective focusing ability of the human visual system and has developed into a core technology in deep learning that improves information processing efficiency and accuracy through dynamic weight allocation. The basic principle is to assign differentiated weights to different parts of the input data, allowing the model to prioritize key information related to the current task. The specific implementation is divided into three steps: first, encode the input data into key value pairs (keys are used to calculate similarity with the query vector, and values represent data content); Then generate weights by calculating the similarity between the query vector (representing the task objective) and each key; Finally, the weights are applied to the values, and the output is obtained by weighted summation, achieving information filtering and focusing. This mechanism is widely used in deep learning, especially in the field of natural language processing (NLP), where it has achieved significant results by focusing on key parts such as keywords and phrases to improve the accuracy of complex text processing; Combining with Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) can enhance sequence modeling and feature extraction capabilities. The Transformer model, as a fully attention based architecture, has made breakthrough progress in NLP tasks and become the current mainstream model. In addition, attention mechanisms have demonstrated strong robustness in computer vision (such as image classification, object detection) and speech recognition (processing long input sequences), optimizing model performance by improving traditional Encoder Decoder frameworks (such as dynamically assigning input sequence weights). With the development of deep learning, the integration of attention mechanisms with new models such as Transformers has become a research hotspot, continuously promoting innovative applications in fields such as time series analysis and financial forecasting, and becoming a key technology to improve model efficiency and accuracy.

3.3. Optimization of Financial Volatility Prediction Using LSTM Attention Fusion

The volatility prediction model is based on a recurrent neural network (RNN) and optimizes the ability to handle long sequence dependencies through gating mechanisms. RNN transmits temporal information through hidden layer states, and its hidden layer h_u is determined by the current input x_u and the preceding hidden layer h_{u-1} , which is in line with the historical influence of financial time series, but faces the problem of gradient vanishing/exploding. On this basis, the Long Short Term Memory (LSTM) network introduces the unit state c , as well as the forget gate Γ^f , input gate Γ^i , and output gate Γ^o . The attention mechanism enhances the ability to focus on key information through dynamic weight allocation. Its principle is to encode the input as a key value pair, calculate the weight based on the similarity between the query vector and the key, and use the weighted sum vector to achieve information filtering. Embedding attention mechanisms in LSTM

(such as embedding attention layers between hidden layers) can automatically assign attention weights to hidden states and optimize feature learning capabilities. The specific framework is shown in Figure 1 Encoder Decoder structure.

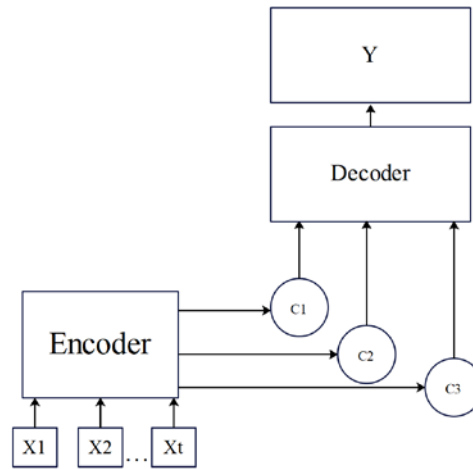


Figure 1 Encoder Decoder Framework

Attention mechanisms can be divided into hard/soft attention, positional attention, input sequence attention, and self attention, among which self attention can rely solely on internal information to extract correlations. The model training uses mean square error (MSE) as the loss function, combined with Adam optimizer to adaptively adjust the learning rate, and Dropout layer to prevent overfitting. In the comparative experiment, the GARCH-LSTM model inputs the volatility features extracted by GARCH (1,1) together with the original sequence into LSTM, further improving its predictive ability. The evaluation indicators include MAE, MSE, MAPE, and trend prediction accuracy, and comprehensively evaluate the goodness of fit of the model. The specific implementation uses the Keras Sequential model to construct a four layer LSTM network, which maps hidden states to outputs through an attention layer to achieve efficient and accurate volatility prediction.

4. Results and discussion

4.1. The principle and application of multi-source data fusion in predicting financial volatility

Multi source data fusion improves the performance of financial volatility prediction by integrating information from different data sources to construct a comprehensive data representation. The basic principle is divided into three steps: in the data preprocessing stage, different sources of data are cleaned, denoised, and normalized to ensure data quality and consistency; The feature extraction and fusion stage extracts representative features from various data sources (such as statistical methods, machine learning, or deep learning techniques), and achieves effective fusion through concatenation, weighted averaging, or complex feature transformation to form a feature set that reflects the multidimensional characteristics of the market; The model training and prediction stage is based on fusion feature training of the model, optimizing parameters to minimize prediction errors, and ultimately achieving reliable prediction. In financial forecasting, multi-source data is widely used - the stock market can integrate social media sentiment analysis (capturing the impact of investor sentiment on price fluctuations), news event extraction (identifying the direct impact of key events such as company mergers and acquisitions, policy adjustments, etc. on the market), and macroeconomic indicators (such as inflation rate, interest rate, GDP growth rate to grasp long-term trends). By integrating these multidimensional information, the model can more accurately capture market dynamic changes, significantly improving prediction accuracy and robustness.

4.2. Model experiment

This study optimized the volatility prediction model through a multi-source data fusion strategy, using web crawling technology to obtain real-time financial text data (such as social media sentiment, news events, macroeconomic indicators). After cleaning, denoising, and normalization preprocessing, dynamic word vectors and semantic features were extracted using the BERT bidirectional Transformer architecture to capture keywords and long-distance dependencies; Synchronously introducing BiLSTM network to achieve bidirectional extraction of text forward and backward semantic dependencies, enhancing the ability to capture temporal features. The model structure adopts a four layer architecture: the input layer receives text data, the BERT layer dynamically generates word vectors as an Embedding layer, the BiLSTM layer fuses bidirectional semantic information, the Dropout layer prevents overfitting, and finally completes the classification task through a fully connected layer. For different data source characteristics (such as differences between long and short texts), a transfer learning strategy is adopted - freezing BERT layer parameters to preserve the ability to extract common features, retraining BiLSTM and fully connected layers to adapt to the semantic relationships of the target dataset, and achieving performance balance. The experiment takes TextCNN as the benchmark, and the comparison shows that the BERT+BiLSTM model has an accuracy rate of 89.3% in the source test set, which is significantly better than the single model and TextCNN. Transfer learning improves the accuracy rate of the target data set to 91.2%, and reduces the training time by 40%. The evaluation indicators used include multi classification accuracy, recall, F1 score, and Kappa coefficient (0.89) to verify the robustness of the model in sample imbalance scenarios. In the iterative experiment, the validation set loss stabilized after the 9th round, avoiding overfitting and confirming the effectiveness of multi-source data fusion and transfer learning.

4.3. Effect analysis

This study optimizes the volatility prediction model through multi-source data fusion and deep transfer learning. In the data preprocessing stage, the source domain dataset (24400 samples) is divided into training/validation/testing sets at a ratio of 7:2:1, and the target domain (4616 samples) is divided at a ratio of 1:1. The dynamic validation set strategy effectively alleviates overfitting. The dataset covers six types of financial entities, including stocks, bonds, and listed companies, with specific distributions shown in "Table 1 Dataset".

Table 1. Dataset Distribution Across Source and Target Domains

Category	Source Training Set	Source Validation Set	Source Test Set	Target Training Set	Target Test Set
Stock	4200	1200	600	500	500
Bond	2800	800	400	500	500
Listed Company	3150	900	450	500	500
Financial Figure	1400	400	200	125	125
Fund	3080	880	440	428	428
Futures	2450	700	350	255	255

Transfer learning reduces the distribution difference between the source domain (such as iShares China Large Cap ETF volatility data) and the target domain through domain adaptation techniques, improving the model's generalization ability. Empirical analysis uses Transformer, Attention LSTM, and Bi LSTM Attention models for comparison. The Transformer model is based on self attention mechanism and processes sequences in parallel through a 6-layer Encoder Decoder architecture (including multi head self attention, residual connection, and layer normalization). The position encoding uses a sine function to capture temporal information. The experimental results show that Transformer has a trend accuracy of 51.43% in predicting the volatility of FXI index funds, significantly better than Attention LSTM (50.76%) and Bi LSTM Attention (51.03%), and has a faster training speed, but requires gradient pruning to prevent memory explosion. Model evaluation metrics include MSE, MAPE, MAE, and trend accuracy. The analysis of the results shows that deep learning models (especially Transformers) outperform traditional GARCH models in dealing with high noise and non-stationary financial time series. The attention mechanism suppresses noise interference through dynamic weight allocation and improves the ability to capture key information. The hyperparameters such as hidden unit dimensions need to be optimized through cross validation to balance complexity and generalization ability. This study validates the effectiveness and superiority of multi-source data fusion, transfer learning, and Transformer architecture in predicting financial volatility.

5. Conclusion

This study integrates deep learning and financial theory to construct a volatility prediction model based on attention mechanism and multi-source data fusion. Its effectiveness and superiority are verified through empirical analysis. The model captures key information in time series through attention mechanism and dynamically weights it, combined with multi-source data fusion to comprehensively characterize the dynamic characteristics of financial markets and improve prediction accuracy. The experimental design covers data preprocessing, evaluation indicator setting, model training optimization, and comparative analysis, highlighting the innovative value. Empirical analysis selected volatility data from multiple financial indices, and the results showed that the model had good predictive performance. The influence of hyperparameters on the prediction results was also explored. Research limitations include: data sources are concentrated in specific markets, and universality and cross market applications need to be verified; Hyperparameter tuning may have limitations and not fully explore the optimal configuration; The deep principles and mechanisms of attention mechanism and multi-source data fusion still need to be further understood. Future directions include: expanding the scope and sources of data to test the generality and robustness of models; Using automatic parameter tuning technology to optimize hyperparameter configuration; Exploring the mechanism of attention and multi-source data fusion in depth through theoretical analysis and experimental verification; Integrating advanced deep learning technology with knowledge in the financial field to develop more accurate and efficient volatility prediction models, providing support for financial market analysis and risk management.

References

- [1] Huang, J. (2025). *Balance Model of Resource Management and Customer Service Availability in Cloud Computing Platform*. *Economics and Management Innovation*, 2(4), 39-45.
- [2] Xu, H. (2025). *Supply Chain Digital Transformation and Standardized Processes Enhance Operational Efficiency*. *Journal of Computer, Signal, and System Research*, 2(5), 101-107.
- [3] Xu Q. *Design and Future Trends of Intelligent Notification Systems in Enterprise-Level Applications*[J]. *Economics and Management Innovation*, 2025, 2(3): 88-94.

- [4] Zhang, Xuanrui. "Automobile Finance Credit Fraud Risk Early Warning System based on Louvain Algorithm and XGBoost Model." In 2025 3rd International Conference on Data Science and Information System (ICDSIS), pp. 1-7. IEEE, 2025.
- [5] Zhou, Y. (2025). Improvement of Advertising Data Processing Efficiency Through Anomaly Detection and Recovery Mechanism. *Journal of Media, Journalism & Communication Studies*, 1(1), 80-86.
- [6] Liu, Y. (2025). The Importance of Cross-Departmental Collaboration Driven by Technology in the Compliance of Financial Institutions. *Economics and Management Innovation*, 2(5), 15-21.
- [7] Zhang M. Discussion on Using RNN Model to Optimize the Accuracy and Efficiency of Medical Image Recognition[J]. *European Journal of AI, Computing & Informatics*, 2025, 1(2): 66-72.
- [8] Xu, H. (2025). Research on the Implementation Path of Resource Optimization and Sustainable Development of Supply Chain. *International Journal of Humanities and Social Science*, 1(2), 12-18.
- [9] Yang D, Liu X. Collaborative Algorithm for User Trust and Data Security Based on Blockchain and Machine Learning[J]. *Procedia Computer Science*, 2025, 262: 757-765.
- [10] Chang, Chen-Wei. "AI-Driven Privacy Audit Automation and Data Provenance Tracking in Large-Scale Systems." (2025).
- [11] Huang, J. (2025). Reuse and Functional Renewal of Historical Buildings in the Context of Cultural Heritage Protection. *International Journal of Humanities and Social Science*, 1(1), 42-50.
- [12] Zhang K. Research on the Application of Homomorphic Encryption-Based Machine Learning Privacy Protection Technology in Precision Marketing[C]//2025 3rd International Conference on Data Science and Network Security (ICDSNS). IEEE, 2025: 1-6.
- [13] Li W. Building a Credit Risk Data Management and Analysis System for Financial Markets Based on Blockchain Data Storage and Encryption Technology[C]//2025 3rd International Conference on Data Science and Network Security (ICDSNS). IEEE, 2025: 1-7.
- [14] Zhou Y. Cost Control and Stability Improvement in Enterprise Level Infrastructure Optimization [J]. *European Journal of Business, Economics & Management*, 2025, 1(4): 70-76.
- [15] Li, W. (2025). Research on Optimization of M&A Financial Due Diligence Process Based on Data Analysis. *Journal of Computer, Signal, and System Research*, 2(5), 115-121.
- [16] Hao, L. (2025). Research on Perception and Control System of Small Autonomous Driving Vehicles. *International Journal of Engineering Advances*, 2(2), 48-54.
- [17] Jing, X. (2025). Research on the Application of Machine Learning in the Pricing of Cash Deposit Products. *European Journal of Business, Economics & Management*, 1(2), 150-157.
- [18] Yang D, Liu X. Collaborative Algorithm for User Trust and Data Security Based on Blockchain and Machine Learning[J]. *Procedia Computer Science*, 2025, 262: 757-765.
- [19] Jing X. Real-Time Risk Assessment and Market Response Mechanism Driven by Financial Technology[J]. *Economics and Management Innovation*, 2025, 2(3): 14-20.
- [20] Liu Z. Research on the Application of Signal Integration Model in Real-Time Response to Social Events[J]. *Journal of Computer, Signal, and System Research*, 2025, 2(2): 102-106.
- [21] Tang X, Wu X, Bao W. Intelligent Prediction-Inventory-Scheduling Closed-Loop Nearshore Supply Chain Decision System[J]. *Advances in Management and Intelligent Technologies*, 2025, 1(4).
- [22] Wu X, Bao W. Research on the Design of a Blockchain Logistics Information Platform Based on Reputation Proof Consensus Algorithm[J]. *Procedia Computer Science*, 2025, 262: 973-981.

- [23] Truong T. *The Research on the Application of Blockchain Technology in the Security of Digital Healthcare Data [J]. International Journal of Health and Pharmaceutical Medicine*, 2025, 5(1): 32-42.
- [24] Gao Y. *Research on Risk Identification in Legal Due Diligence and Response Strategies in Cross border Mergers and Acquisitions Transactions [J]. Socio-Economic Statistics Research*, 2025, 6(2): 71-78.