A Large Model for Forecasting Volatility of Financial Products Based on Multimodal Data

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November 11, 2024

Abstract

Multi-modal data in financial markets are heterogeneous, and different types of data are different in format, structure and standard, which leads to poor forecasting effect and large error in forecasting the volatility of large model products. In this paper, a large model of financial product volatility prediction based on multimodal data is proposed. Firstly, the multi-source information such as text, image, sound and transaction data is integrated to analyze the source of multi-modal data, and the multi-modal data is fused by linear weighting algorithm. Then, according to the data fusion results, the multimodal data are preprocessed. Finally, the characteristics of financial product volatility prediction are extracted and used as the input of blockchain financial product forecasting model to realize financial product volatility prediction. The experimental results show that this method can effectively improve the forecasting effect of financial product volatility, and the forecasting error varies from 0.02 to 0.25, and the forecasting error is always low, showing significant advantages in forecasting diversity and relatively high contribution.

Keywords: Multimodal data; Financial products; Volatility; Predicting the big model

1 Introduction

In today's complex and changeable financial market, it is of great significance for investors, financial institutions and policy makers to accurately predict the volatility of financial products [?]. Volatility, as an important indicator to measure the price fluctuation of financial assets, not only reflects the risk level of the market, but also directly affects the decision-making behavior of investors and the pricing mechanism of financial products [?, ?]. With the rapid development of information technology, the application of multimodal data in the volatility prediction model of financial products is gradually becoming a research hotspot [?, ?]. As a data set containing various types of information, such as images, texts, audio and video, multimodal data has the characteristics of diversity, complementarity and complexity [?]. These data come from different sensory channels and describe the same object or event together, which provides more comprehensive and rich information input for the prediction of financial product volatility.

Reference [?] puts forward a large prediction model of the influence of financial derivatives on financial risks. This paper analyzes the subtle influence of financial derivatives on the risk pattern of China's financial market, and emphasizes the dual necessity of using financial innovation to promote market development and strengthening the financial structure to resist potential shocks. Using the designed model, this paper analyzes the performance of Shanghai and Shenzhen 300 stock indexes in recent years, trying to clarify the efficacy of financial derivatives in risk regulation. It also predicts the future risk trajectory and contributes to the discussion on cultivating an elastic and progressive financial ecosystem in China. However, the financial derivatives market usually has high volatility, especially futures and its related derivatives, and its mechanisms such as T+0 and leveraged trading aggravate market risks. This high volatility may lead to a large error in the prediction of the model.

Reference [?] puts forward the management prediction model of derivative financial products in banking activities. On the statistical level, through the concretization of econometric model, and on the theoretical level, observation and analysis. The whole discussion looks at the main derivatives and how they are used and integrated into the banking industry. Another goal is to deepen the impact of derivative financial products on systemic risk and monetary policy at least in theory. However, there are nonlinear relationships among many factors in the derivatives market, which makes it more difficult for the model to capture these relationships, and then the forecasting performance will be affected.

Reference [?] Using the framework of financial ability, this paper evaluates the role of structure, interaction and behavior prediction factors in influencing financial well-being. The data used in this study comes from financial well-being survey and structural equation modeling technology. The results show that savings habits and quantity (i.e. behavioral factors) are more closely related to financial well-being than financial shocks, income fluctuations and the use of financial products (i.e. structural or interactive factors). These findings show that efforts to promote financial capacity and thus improve financial well-being should not ignore behavior-oriented financial education and intervention programs and policies to encourage household savings at all income levels. However, the volatility prediction model of financial products is too complex and contains too many parameters or variables, which leads to the model performing well on training data, but its generalization ability on new data is poor.

Reference [?] puts forward: Research on volatility modeling and forecasting of China financial market based on new decomposition methods, and reconstructs several new heterogeneous autoregressive realized volatility models by using various volatility decomposition methods and embedding Markov mechanism models. However, with the continuous development and changes of the financial market, the model needs to be constantly updated to adapt to the new market environment. The model can not update or adjust its structure and parameters in time, which leads to the decline of prediction performance.

Although the above research has made some progress, however, the volatility prediction of financial products is also facing many challenges. Multimodal data is heterogeneous, and different types of data have differences in format, structure and standards. It is necessary to adopt complex data preprocessing and feature extraction techniques to achieve unified representation and effective integration of data. There are redundancies, conflicts and noises among multimodal data, so data cleaning and integration are needed to ensure the quality and consistency of data. How to design a reasonable model structure to make full use of the complementary information in multimodal data and improve the prediction performance of the model is also a major problem in current research. In order to meet these challenges, this paper constructs a large model of financial product volatility prediction based on multimodal data. The model will make full use of the performance of multi-modal data and realize the accurate prediction of financial product volatility.

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2 Introduction

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3 Multimodal Data Fusion and Preprocessing

3.1 Data Sources

Data source is an important part of building a large model for predicting the volatility of financial products. Data sources cover many aspects and can capture many factors that affect the volatility of financial products. The main data sources are shown in Figure 1.

According to Figure 1, the specific schematic diagram of data sources is shown in Figure 1.

1. **Text data**

    - *News reports*: Articles from financial news websites, traditional media and online news aggregation services, which contain information about economic indicators,

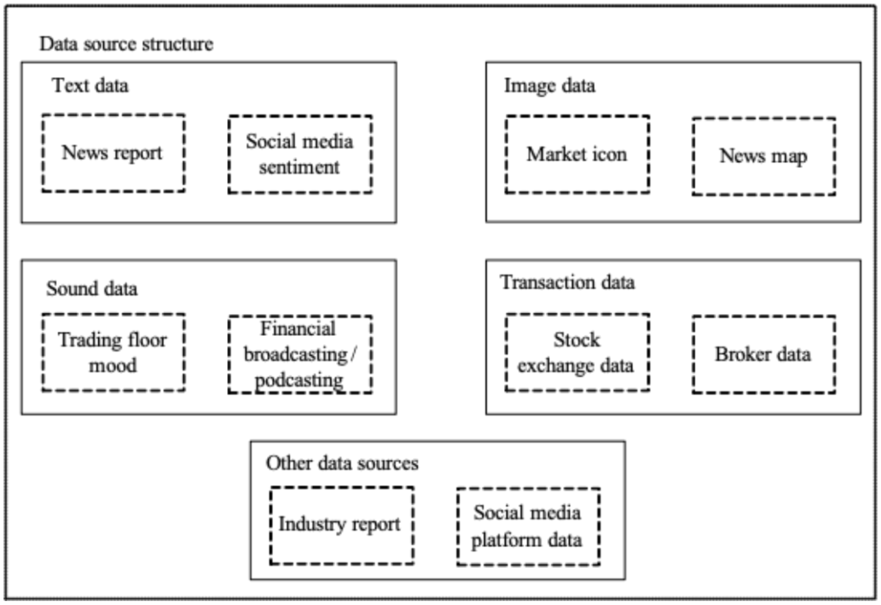

Figure 1: Schematic diagram of data source

policy changes, company performance and so on, and have a direct impact on the financial market [?].

- *Social media sentiment*: User comments and posts captured from social media platforms such as Weibo, Twitter and Reddit are used to extract market sentiment, which is one of the important factors affecting the fluctuation of financial products.

2. **Image data**

    - *Market charts*: Including price trend charts, volume charts and technical index charts of stocks, bonds and commodities, etc. These charts provide intuitive market dynamic information and can extract features through image recognition or computer vision technology.
    - *News map*: News map can sometimes reflect the changes of market events or emotions and can be used as an auxiliary data source.

3. **Sound data**

- *Trading floor mood*: If possible, record audio from the trading floor and evaluate the emotional state of traders through sound analysis technology.
- *Financial Broadcasting/Podcasting*: Discussions and comments in financial broadcasting and podcasting may also contain useful information about market trends.

4. **Transaction data**

- *Stock exchange data*: Real-time and historical trading data of financial products such as stocks, futures and options directly obtained from the stock exchange, including opening price, closing price, highest price, lowest price and trading volume.
- *Broker data*: Transaction data obtained through financial brokers or trading platforms, which contain more detailed transaction information, such as order flow and trader behavior.

5. **Other data sources**

- *Industry report*: Industry research reports from consulting companies and research institutions, including market trends, competition patterns and other information of specific industries.
- *Social media platform data*: In addition to the above-mentioned social media emotions, we can also use user behavior data (such as likes, shares, concerns, etc.) on social media platforms to analyze market attention.

Multimodal data is a collection of multi-source heterogeneous data, where different sources and types of data are fused using various encoding methods and models, resulting in a new modality [**?**]. The architecture of multimodal data relies on fusion and analysis technologies [**?**]. The primary goal is to encode, transform, and process different types of data efficiently through machine learning and traditional techniques to enable deep data mining [**?**, **?**]. Based on the extensive multi-source data, a data source matrix F is defined as:

$$F = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{1}$$

Where F represents the set data source matrix; f_x and f_y respectively represent sparse points mined in different horizontal directions; c_x and c_y respectively represent the fused data in different horizontal directions.

2.2 Data fusion method

In order to generate a group of new modes, the data of different modes are required to have certain compatibility or similarity in feature space, and at the same time, the features of each mode are preliminarily processed before fusion. Because the collected data of financial product volatility forecast come from many methods and show multimodal characteristics, it can not be directly and uniformly applied, so the linear weighting algorithm is used to fuse the multimodal data, which is convenient for building a large model.

Taking the fluctuation data of financial products as an example, the weighted average filtering algorithm is used to clean it, that is, to remove noise data. The formula is as follows:

$$S'(t) = \frac{a_1 S(t-1) + a_2 S(t) + a_3 S(t+1)}{F(a_1 + a_2 + a_3)} \tag{2}$$

Where $S'(t)$ represents modal data after cleaning; $S(t-1)$ and $S(t+1)$ represent the adjacent modal data of $S(t)$; a_1, a_2, and a_3 represent the weight coefficients of $S(t-1)$, $S(t)$, and $S(t+1)$.

Multi-modal data are different in dimensions, so it is impossible to fuse them directly. Therefore, the maximum and minimum standardization method is used to remove the adverse effects of dimensions, and the multimodal data is converted into values within the $[0, 1]$ range. The formula is as follows:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

Where X' stands for normalized modal data; $X_{\max}$ and $X_{\min}$ represent the maximum and minimum value functions respectively.

According to the principles of Equations (1) and (2), other modal data are cleaned and standardized to obtain noise-free and dimensionless multimodal data. The linear weighting algorithm is used to fuse multimodal data, and the formula is as follows:

$$Y = w_1 X_1 + w_2 X_2 + w_3 X_3 + \cdots + w_n X_n + c \tag{4}$$

Where Y represents the fusion result of multimodal data; $w_1, w_2, w_3, \ldots, w_n$ represent the fusion weight factors corresponding to multimodal data; c stands for the offset term.

According to the above calculation results, the data fusion result is obtained, and the formula is as follows:

$$H(D) = H(X) - H(Y|X) \tag{5}$$

Where $H(D)$ represents the information entropy of the historical data set D of equipment operation state; $H(Y|X)$ represents the conditional entropy of modal data in the historical data set D; $H(X)$ represents the standardized parameter of the fusion weight factor.

According to Equation (5), the effective fusion of multimodal data is completed, which provides more comprehensive, accurate, and reliable data support for equipment operation.

3.2 Multimodal data preprocessing

Based on the fused multimodal data, the multimodal data is preprocessed. In order to preprocess the multimodal data, it is assumed that the multimodal data is located in the terminal cloud storage space, and the random points in the space are x_i-fitted. The processing process is as follows:

$$P(x) = D_F \times \sum_{k=0}^{M} K_k \tag{6}$$

Where $P(x)$ stands for denoising of multimodal data; K_k stands for data edge smoothness; M stands for data order. On this basis, the data processing process is regarded as the conversion process of set parameters, that is, the process of realizing the gradual progress of data set to expected data set. This process is as follows:

$$Y_{ij} = Z \times X_{ik} \times P(x) \tag{7}$$

Where Y_{ij} represents expected data; i represents the number of objects; j represents the feature number of the processed data; i and j are positive integers; Z stands for conversion condition; X_{ik} represents the display data set. The value of Y_{ij} output after conversion should be greater than that of X_{ik}. According to the above method, the data spatial dimension is converted to realize multimodal data preprocessing, and the results are as follows:

$$e_q = \frac{1}{2}\sqrt{(\omega_i - Y_{ij})^2} \tag{8}$$

Where Y_{ij} represents Weight values.

4 Construction of a Large Model for Forecasting Volatility of Financial Products

In the prediction space, the relationship between data may be clearer and easier to capture. For example, some features of great significance in the financial market (such as seasonal patterns, periodic changes, the impact of unexpected events, etc.) may be more easily identified and extracted in the forecasting space. Based on the preprocessed multimodal data, data conversion is carried out by considering the characteristics of the data, the complexity of the model and the requirements of the prediction task.

Assuming the pre-prediction space V containing m multimodal data, the formula is as follows:

$$H = e_q = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1n} \\ h_{21} & h_{22} & \cdots & h_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ h_{m1} & h_{m2} & \cdots & h_{mn} \end{bmatrix} \tag{6}$$

Where n represents the number of attributes with the most predicted data, the row of the matrix describes that the space before prediction contains the target, and the column describes the multi-modal data attributes. If the target does not contain an attribute, the corresponding value is 0. The matrix can clearly see the relationship between the prediction target and each data attribute. The current measurement space is as follows:

$$G = H \times \begin{bmatrix} g^s_{11} & g^s_{12} & \cdots & g^s_{1u} \\ g^s_{21} & g^s_{22} & \cdots & g^s_{2u} \\ \vdots & \vdots & \ddots & \vdots \\ g^s_{l1} & g^s_{l2} & \cdots & g^s_{lu} \end{bmatrix} \tag{7}$$

Where g^s_{ij} represents the j data obtained by the information source i from the prediction model; u represents the maximum data provided by each information source; l represents the total number of data sources. At this time, the prediction space N_f is as follows:

$$K = H \times \begin{bmatrix} k_{q11} & k_{q12} & \cdots & k_{q1c} \\ k_{q21} & k_{q22} & \cdots & k_{q2c} \\ \vdots & \vdots & \ddots & \vdots \\ k_{qb1} & k_{qb2} & \cdots & k_{qbc} \end{bmatrix} \tag{8}$$

In the formula, b and c represent the mapping coefficient, n_{ij}^s represents the data mapped to the prediction space, and the mapping relationship obtained by simultaneous formula (10) and formula (11) is as follows:

$$N_f = \frac{G \times K}{\Delta t \times \beta} \tag{9}$$

Where Δt represents data time interval and β represents prediction times. Equations (10) and (11) describe the current measurement space and the prediction space, and the mapping relationship N_f between them is obtained simultaneously, thus realizing the transformation from the original data space to the prediction space.

Feature extraction based on the transformed data. The characteristics of historical volatility data, macroeconomic and market factors, technical indicators and quantitative analysis are analyzed respectively, as shown in Table 1.

Table 1: Description Table of Volatility Prediction Characteristics of Financial Products

Predictive feature category	
Historical volatility data	Standard deviation or
Macroeconomic and market factors	Including economic growth rate, inflation rate, interest r
Technical indicators and quantitative analysis	Quantitative indicators obtained l

Combined with Table 1, the features useful for predicting the volatility of financial products are extracted from multimodal data sources. Usually, the standard deviation of price changes of financial products in the past days is used to measure historical volatility, which provides statistics of past price changes of financial products and helps to identify seasonal patterns, periodic changes and the impact of emergencies. To extract features, the expression is as follows:

$$H_v = \sqrt[\frac{1}{N-1}]{N_f \sum_{i=1}^{N} (P_i - \overline{P})^2} \tag{13}$$

Where P_i represents the price on the i day; $\overline{P}$ represents the average price in the past N days.

From this information, the above-mentioned key features are taken as the input of the big model, so as to realize the volatility prediction of financial products. The blockchain financial product prediction model is shown in Figure 2.

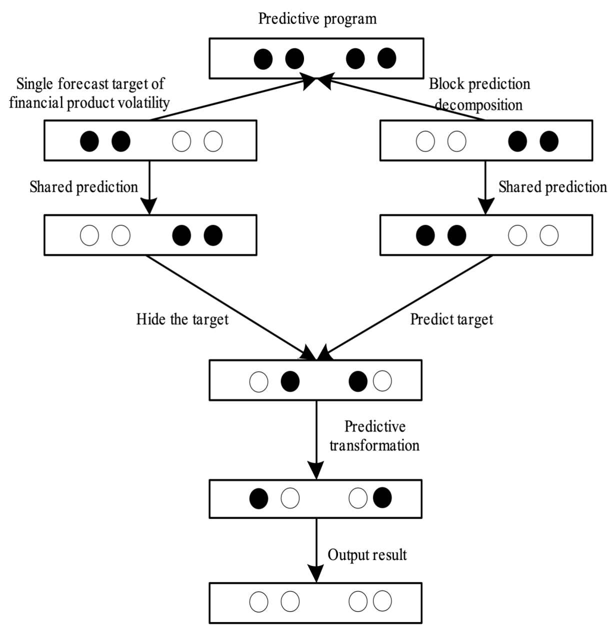

Figure 2: Blockchain Financial Product Forecasting Model

On the basis of Figure 2, in order to build an efficient financial product volatility forecasting model and establish a unified forecasting target, which should clearly define the volatility type and its time range, and then determine the forecasting accuracy by selecting appropriate parameters of the correlation forecasting model, the formula is as follows:

$$E_{RTF} = D_R \times J_{HH} \times U_{IH} \times H_v \tag{14}$$

Where E_{RTF} represents the prediction accuracy; D_R indicates the difference of feature prediction; J_{HH} represents the strain prediction range; U_{IH} indicates the number of predictions. On this basis, a model that can accurately predict the volatility of financial products is trained by using multimodal data, which provides strong support for financial decision-making:

$$J_{HG} = 1 - \frac{d_F}{E_{RTF}} \tag{15}$$

In the formula, d_F represents the dimension of the design index of the large model of financial product volatility prediction. According to the above calculation, the forecast result of financial product volatility is output.

5 Experimental Analysis

5.1 Experimental Environment

In order to verify the overall effectiveness of the large model of financial product volatility prediction based on multimodal data, experiments were carried out. According to the processing steps of this method in the construction of financial product volatility prediction model, the experiment is divided into three parts: repetitive data cleaning, multimodal data fusion and data labeling. In the repetitive data cleaning, multimodal data with repetitive data ranging from 20GB to 220GB are used as experimental data, while in the multimodal data fusion, 10,000 real data are used as experimental data, and the data labeled with this method is used as experimental data. The experimental environment is shown in Figure 3.

Set the experimental parameters in the above experimental environment, as shown in Table 2.

5.2 Experimental Index

On the basis of the above experimental environment and parameters, the experimental analysis is carried out. The experimental indicators choose prediction accuracy and prediction error as evaluation indicators, and the formula is as follows:

$$Z_h = \frac{1}{n}(v - v') \times 100\% \tag{16}$$

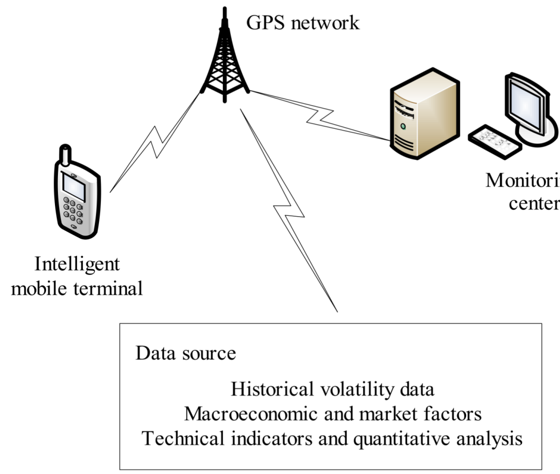

Figure 3: Experimental environment diagram

Table 2: Table of Experimental Related Parameters

Serial number	**Parameter**	**Numerical value**
1	Processor	AMD Ryzen Threadripper 16 core 3.5GHz
2	Internal storage capacity	64 GB DDR4 ECC RAM
3	Memory speed	3200 MHz
4	Window minimum	2
5	Maximum window value	500
6	Number of hidden layer nodes	64
7	Batch size	128
8	Number of training rounds	40
9	Kernel function	RBF kernel
10	Penalty coefficient	0.1

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{x_i - y_i}{y_i}\right| \times 100\% \tag{17}$$

Where Z_h represents the prediction accuracy, and $MAPE$ is the Mean Absolute Percentage Error.

Where n represents the number of financial product volatility forecast items; V represents the total number of forecasts; v' represents the actual quantity of the forecast. M represents the predicted data length; x_i represents the data value after prediction, y_i represents the real value of the data before prediction, and $\overline{y}_i$ represents the average value of the real value. The higher the prediction accuracy and the smaller the prediction error, the higher the data quality after prediction.

In order to meet the validity of the large-scale model for forecasting the volatility of financial products, the prediction effects of the traditional single data source model and the multi-modal data fusion model need to be diversified, and the calculation formula is as follows:

$$X = 1 - \frac{simS_{\alpha\beta}}{\sigma_i} \tag{18}$$

Where $simS_{\alpha\beta}$ represents the similarity between α and β defined in the interval $[0, 1]$; σ_i represents the total number of diversity factors.

In order to further verify the effect of the large model of financial product volatility prediction based on multimodal data, the prediction effect is analyzed by contribution degree. Among them, the contribution degree refers to the role and value of multimodal data in predicting the volatility of financial products. These multimodal data, through their respective characteristics and correlation, work together on the prediction model to improve the accuracy, stability, and generalization ability of the prediction. Analyze the proportion of financial products predicted under the application of the research prediction model to all products in the test sample set. The higher the contribution, the more comprehensive the prediction and the better the effect. The contribution formula is as follows:

$$V = \frac{U_i}{\psi} \times 100\% \tag{19}$$

Where U_i represents the predicted financial product; ψ stands for the test sample set of financial products.

6 Analysis of Experimental Results

Taking the method in this paper as an experimental method, and comparing the methods in reference [7], reference [8] and reference [9], the accuracy of volatility prediction of financial products by the four methods is analyzed, and the specific results are shown in Figure 4.

From the analysis of Figure 4, it can be seen that the forecast accuracy of financial product volatility by this method has obvious advantages, which is always higher than that by reference [7], reference [8] and reference [9], and the highest forecast accuracy of financial product volatility can reach 99.98%, indicating that this method can effectively improve the forecast effect of financial product volatility.

In order to verify the forecasting effect of this method in financial product volatility, the forecasting errors of reference [7] method, reference [8] method, reference [9] method and this method are analyzed, and the specific results are shown in Figure 6.

By analyzing Figure 6, it can be seen that the forecast error of financial product volatility by reference [7] ranges from 0.51 to 0.94, by reference [8] from 0.45 to 0.86, and by reference [9] from 0.43 to 0.75, while the method presented in this paper achieves an error range of 0.02 to 0.25. The proposed method maintains a consistently low prediction error across various iterations, with the slowest error growth rate, significantly outperforming the methods in references [7], [8], and [9]. This stability demonstrates the robustness and high accuracy of the proposed approach.

According to Equation (19), the comparison results of prediction diversity between the traditional single data source model and the multimodal data fusion model are shown in Table 3.

As can be seen from Table 3, the predicted diversity index values of the multi-modal data fusion model are higher than those of the traditional single data source model. This difference is more significant in the cases with higher serial numbers, indicating that the performance advantage of the multi-modal model increases as data complexity and volume grow. Simultaneously, the forecast diversity index values for both models exhibit a steady upward trend, demonstrating that the forecasting capabilities of both models improve as conditions evolve, particularly for the multi-modal data fusion model.

To summarize, compared to the traditional single data source model, the multi-modal data fusion model shows significant advantages in forecasting diversity. This highlights that integrating information from various data sources enables the model to capture more diverse features and patterns, thereby enhancing both the accuracy and diversity of forecasting results.

Taking the method from reference [7], the method from reference [8], and the method from reference [9] as comparison points, the contribution comparison results between those methods and the method proposed in this paper are shown in Figure **??**.

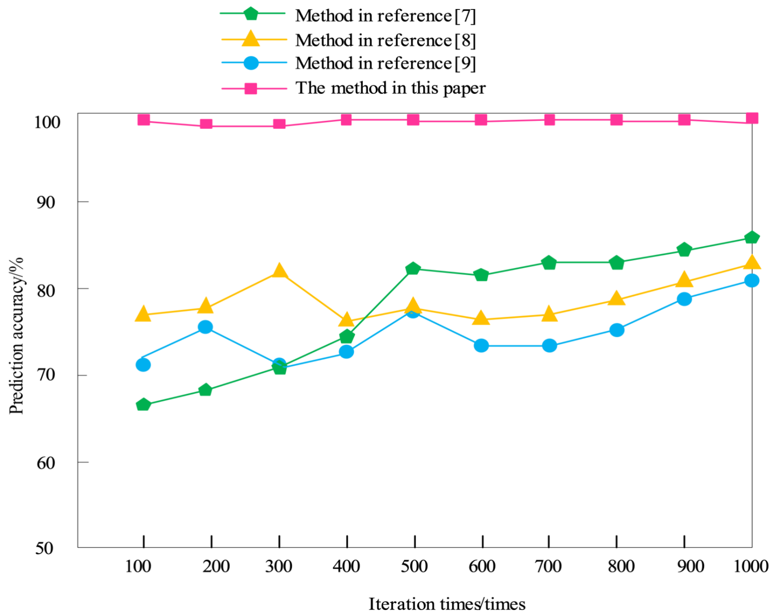

Figure 4: Comparison results of forecasting accuracy of financial product volatility under different methods.

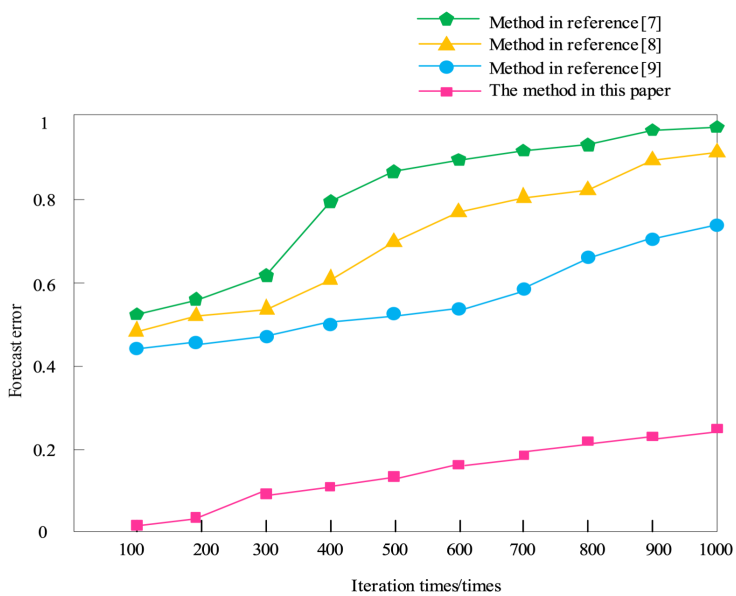

Figure 5: Comparison results of volatility prediction errors of financial products under different methods.

Table 3: Comparison results of prediction diversity between traditional single data source model and multimodal data fusion model

Serial number	Traditional single data source model	Multimodal data fusion model
1	0.78	0.82
2	0.79	0.84
3	0.80	0.86
4	0.81	0.87
5	0.82	0.90
6	0.83	0.92
7	0.84	0.93
8	0.85	0.95
9	0.86	0.97
10	0.87	0.99

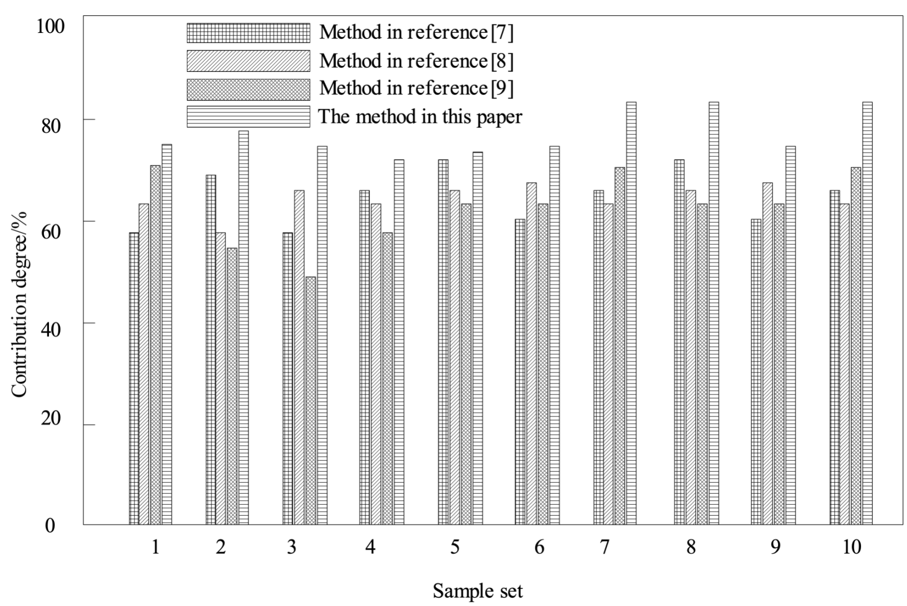

Figure 6: Comparison results of contribution of different methods.

7 Conclusion

This paper proposes a large model for financial product volatility prediction based on multimodal data. By analyzing and integrating multimodal data, a model capable of capturing complex market dynamics and enhancing prediction accuracy is constructed. This not only enriches the theoretical framework for financial product volatility prediction but also provides robust technical support for risk management in real-world financial markets. The experimental findings lead to the following conclusions:

1. The proposed method effectively enhances the forecasting of financial product volatility.

2. The forecast error using this method ranges from 0.02 to 0.25, consistently demonstrating low error rates and achieving reliable forecasting performance.

3. Compared with traditional single data source models, the multimodal data fusion model exhibits clear advantages in prediction diversity. This advantage underscores that integrating information from various data sources enables the model to capture more diverse features and patterns, thereby improving prediction accuracy and diversity.

4. The contribution level of this method is relatively higher, highlighting its effectiveness in improving the forecasting of financial product volatility.

References

[1] Dankwah, J. B., Abubakari, A. R., & Bunyanso, S. (2022). Patronage of insurance products and financial literacy nexus: an emerging market perspective. *EuroMed J. of Management*, 4(2), 90-100.

[2] Magner, N. S., Hardy, N., Ferreira, T., et al. (2023). "Agree to Disagree": Forecasting Stock Market Implied Volatility Using Financial Report Tone Disagreement Analysis. *Mathematics*, 11(7), 1-16.

[3] Economics, C. (2024). Scenario Generation for Financial Data with a Machine Learning Approach Based on Realized Volatility and Copulas. *Computational Economics*, 12(12), 1-10.

[4] Huang, J., Chen, B., Xu, Y., et al. (2023). Time-frequency Volatility Transmission among Energy Commodities and Financial Markets during the COVID-19 Pandemic: A Novel TVP-VAR Frequency Connectedness Approach. *Finance Research Letters*, 53, 103634.

[5] Yazdani, S., Hadizadeh, M., & Fakoor, V. (2022). Computational analysis of the behavior of stochastic volatility models with financial applications. *Journal of Computational and Applied Mathematics*, 411, 1-12.

[6] Ziani, S. (2024). Enhancing fetal electrocardiogram classification: A hybrid approach incorporating multimodal data fusion and advanced deep learning models. *Multimedia Tools and Applications*, 83(18), 55011-55051.

[7] Wang, W. (2024). Forecasting and Assessing the Impact of Financial Derivatives on Financial Risk. *Journal of Financial Risk Management*, 13(2), 325-332.

[8] Radulescu, C. V., Dima, C., Gaf-Deac, I., et al. (2024). Management of Derivative Financial Products within the Banking Activity. *Proceedings of the International Conference on Business Excellence*, 18(1), 945-954.

[9] Anvari-Clark, J., & Ansong, D. (2022). Predicting Financial Well-Being Using the Financial Capability Perspective: The Roles of Financial Shocks, Income Volatility, Financial Products, and Savings Behaviors. *Journal of Family and Economic Issues*, 43, 730-743.

[10] Ma, F., He, X. F., & Lu, X. J. (2023). Modeling and prediction of Chinese stock market volatility: Based on a new decomposition method. *Systems Engineering - Theory & Practice*, 43(10), 2827-2845.

[11] Abd El-Naby, A., Hemdan, E. D., & El-Sayed, A. (2023). An efficient fraud detection framework with credit card imbalanced data in financial services. *Multimedia Tools and Applications*, 82(3), 4139-4160.

[12] Zhao, Y., Zhao, J., & Lam, E. Y. (2024). House Price Prediction: A Multi-Source Data Fusion Perspective. *Big Data Mining and Analytics*, 7(3), 603-620.

[13] Jiang, Z. R., & Li, Y. N. (2024). Mathematical Modeling of Secure Access to Multimodal Heterogeneous Network Data Across Layers. *Computer Simulation*, 41(4), 475-479.

[14] Parisi, L., & Manaog, M. L. (2023). Innovative feature-driven machine learning and deep learning for finance, education, and healthcare. *Neural Computing & Applications*, 35(16), 11477-11480.

[15] Jiang, Y. (2022). Application and Comparison of Multiple Machine Learning Models in Finance. *Scientific Programming*, 2022(8), 1-9.