ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on Financial Asset Price Prediction Based on Temporal Feature Learning

Bowei Zhang[1,*]

[1] Shanghai University of Finance and Economics, Shanghai 200433, Shanghai, China

SUMMARY: *Against the backdrop of the rapid development of digitalization and quantitative trading in financial markets, time-series data of financial asset prices has grown exponentially. Accurate prediction of price changes has become the core support for risk management, asset allocation and investment decision-making. Aiming at the problems that traditional statistical models struggle to capture nonlinear dependencies, existing deep learning methods ignore multi-scale temporal features and dynamic cross-asset correlations, and the mining of the coupling relationship between market sentiment and prices is insufficient, this paper proposes a financial asset price prediction method based on temporal feature learning, and constructs an integrated framework of "multi-scale temporal decomposition - cross-asset correlation modeling - sentiment-price collaborative learning - incremental feedback optimization". Experiments were carried out based on 1.26 billion daily and hourly frequency data of CSI 300 constituent stocks, S&P 500 constituent stocks and Bitcoin. The results show that the model achieves a single-day rise and fall prediction accuracy of 78.2%, a Mean Absolute Error (MAE) of 0.85, a Root Mean Square Error (RMSE) of 1.12, a cross-asset linkage prediction recall rate of 83.5%, and a processing time of 1.8 hours for one million pieces of data. The approach can be exceptionally efficient when it comes to the accuracy of predictions, its long-term stability and generalization across markets as well as being able to offer a quantitative basis of making decisions that financial market participants may rely on.*

KEYWORDS: *Temporal Feature Learning; Financial Asset Price Prediction; Multi-scale Decomposition; Cross-asset Correlation; Sentiment Perception; Incremental Learning*

1 Introduction

Since the close ties of the world financial markets and the spread of electronic trading, it has been possible to generate large amounts of high dimensional time series data on various financial instruments including stocks, bonds, commodities and cryptocurrencies. The data are filled with intricate details including the relationship between market supply and demand, the behavior of investors, macroeconomic effects and risk transfer, and their variations in price have standard features of nonlinearity, non-stationarity, severe noise and multi-scale variability. Precise forecast of financial asset price changes can be used not only to assist investors in optimizing asset allocation and minimizing investment risks, but also to offer data assistance to regulatory bodies in order to stabilize the market. Nevertheless, the intricacy and unpredictability of financial markets cause the prediction of prices to remain an enduring problem in the academic and business environment.

---

*2023111546@stu.sufe.edu.cn

https://doi.org/10.65102/is20261030

The classical approaches to financial prediction are largely founded on statistical econometric models that have their limitations especially in the financial time series prediction that cannot be entirely adaptable to the dynamic nature of financial data. The introduction of machine learning solutions has seen the implementation of models like Support Vector Machine (SVM) and Random Forest in price prediction. They perform better in nonlinear fitting than traditional statistical models, however, the manual feature engineering is used, and it is hard to extract deep temporal patterns automatically.WANG Junhao [1] integrated CNN and LSTM models, combining image features and temporal dynamics, to improve the accuracy of single-asset stock price prediction, providing a typical paradigm for the application of deep learning in financial time-series prediction; Uygun Y et al. [2] systematically evaluated the performance of graph neural network-based temporal deep learning models in financial asset price prediction, verifying the effectiveness of graph structure modeling for correlation feature extraction; LIU Zhihan [3] proposed a multi-scale financial data prediction method based on sequence decomposition, providing a new technical path for multi-scale feature extraction; Karanasos M et al. [4] studied the short- and long-run cyclical variation of cross-asset relationships, revealing the heterogeneous characteristics of asset linkages at different frequencies; Andri A et al. [5] evaluated the impact of weight initialization on recurrent and Transformer models in financial asset price prediction, providing detailed references for model optimization; ZHANG Yu [6] conducted research on financial asset price prediction using machine learning methods, further verifying the applicability and limitations of traditional machine learning models in financial forecasting; JIN Ye [7] proposed a temporal agglomerative clustering method for securities entities, providing a new technical means for asset correlation analysis; ZHAI Mingrui [8] focused on the prediction of cross-period spread of treasury bond futures, adopting the idea of combining traditional econometrics and machine learning, providing a new practical reference for the prediction of single-category financial assets; LI Haodi [9] constructed an ARIMA-Transformer-GNN hybrid model, combining traditional statistical models with deep learning models, and applied it to the prediction of CSI 300 stock index futures, verifying the advantages of the hybrid model in capturing linear and nonlinear features.

In recent years, deep learning technology has brought new breakthroughs to financial time-series prediction.Papavassiliou G V [10] focused on the problem of cross-asset contagion in times of stress, laying a theoretical foundation for cross-asset correlation modeling; Hou M [11] studied the construction of financial market sentiment index and its predictive power for asset prices, confirming the close correlation between market sentiment and price changes; Enguo G [12] discussed the inherent law of the unpredictability of financial asset price fluctuations, pointing out that multistability and chaos are the essential characteristics of financial markets; Shen F et al. [13] proposed an enhanced risk-aware multi-task learning framework integrating dual-source sentiment and multi-scale decomposition, which was applied to stock ranking prediction, achieving the collaborative improvement of prediction accuracy and risk control; Yang R et al. [14] proposed an attention fusion-based multi-scale decomposition network, further improving the multi-scale feature fusion technology; CHEN Shiting [15] conducted research on stock prediction and dynamic portfolio based on multi-scale decomposition, extending the prediction results to the investment decision-making level; Wang J et al. [16] adopted a multi-scale decomposition learning model to predict LNG prices, verifying the applicability of multi-scale methods in commodity prediction; Xu X et al. [17] realized hybrid forecasting of carbon emission prices in China based on multimodal data feature fusion and multi-scale decomposition strategy, expanding the application scenarios of multi-scale methods; LI Haodi [18] further verified the robustness of the ARIMA-Transformer-GNN hybrid model under different market environments; Wang J et al. [19] proposed a two-stage deep ensemble paradigm based on optimal multi-scale decomposition and multi-factor analysis, significantly improving the stability of stock price prediction; BI Junyu [20] studied the multi-factor-based intelligent stock selection algorithm, providing practical technical support for quantitative investment.

The paper will choose six representative works which are summarized and combined according to the substituted relevant references that focus on the most important directions, namely, single-asset prediction, multi-scale decomposition, cross-asset correlation and sentiment fusion. The exact description is presented in Table 1.

Table 1: Overview of Related Studies

Reference	Research Content	Technical Approach	Application Scenario	Characteristics and Limitations
[1]	Single-asset stock price prediction	Integration of CNN and LSTM models	Stock market	Integrates image and temporal features with strong fitting ability, but does not consider cross-asset correlations
[3]	Multi-scale financial data prediction	Sequence decomposition method	Multiple types of financial assets	Effective in multi-scale feature extraction, but lacks deep fusion of sentiment and temporal features
[7]	Temporal clustering and correlation analysis of securities entities	Temporal agglomerative clustering method	Securities market	Excellent clustering effect, but not extended to price prediction with limited practicality
[10]	Cross-asset risk contagion prediction	Traditional econometric analysis method	Multi-type financial asset markets	Accurate in depicting risk contagion, but mainly static analysis with no dynamic update mechanism
[13]	Stock ranking prediction and risk control	Risk-aware multi-task learning + sentiment fusion + multi-scale decomposition	Stock market	Good multi-feature fusion effect, but does not involve cross-asset linkage modeling
[20]	Intelligent stock selection and asset allocation	Multi-factor algorithm	Stock market	High stock selection accuracy, but not combined with temporal features with insufficient short-term prediction performance

The current findings of research studies have facilitated the further development of the financial time-series prediction discipline, though there remain numerous limitations on their practical use in the real financial market that is intricate and unpredictable. To begin with, financial price time series are multi-scale which means that they include trend terms, periodic terms, and noise terms, and single-scale modeling is not able to represent the fluctuation laws of various time scales. Secondly, the correlation between assets is not constant; it will be greatly affected by macroeconomic factors and market sentiment, and static graph structures cannot properly represent this dynamic correlation. Third, complex nonlinear coupling relationship exists between market sentiment and price changes. The majority of available approaches consider sentiment as a separate feature that can be spliced and do not provide the depth of collaborative learning between the two. 4. Financial market structures are changing dynamically and static models trained models will degrade in performance after some time without an efficient incremental update system.

According to what has been discussed above, the paper suggests a temporal feature learning mechanism that combines multi-scale temporal decomposition with dynamic cross-asset correlation modeling, sentiment-price collaborative learning and incremental feedback optimization to predict changes in the financial asset prices. The proposed method can accomplish all the steps of multi-scale feature extraction, cross-asset relationship modeling, sentiment semantic fusion and price trend forecasting within a single framework, offering a novel technological solution of precise forecasting of financial asset price changes.

2 Materials and Methods

2.1 Temporal Feature Modeling Method Based on Multi-scale Decomposition and Dynamic Cross-asset Correlation

The financial asset price time series are an archetype of multi-scale non-stationary signals; the fluctuations on various time scales represent the various market driving factors, which are long-term trends that indicate macroeconomic and industry development, medium-term cycles indicating market sentiment and capital movements, and short-term fluctuations that are controlled by trading behavior and noise. At the same time, the financial market is a complicated correlation system, and the price of an individual asset would spread to the rest of the assets via industrial chains, capital chains and sentiment chains. Hence, it is important to do both multi scale temporal decomposition and dynamic cross asset correlation extraction at the feature modeling stage, allowing the model to encompass all inner laws of the price changes and outer influences.

To clearly present the processing path of financial time-series data before entering the large model and illustrate the correlation between multi-scale decomposition, correlation graph construction and feature fusion, Figure 1 shows the overall workflow of temporal feature modeling. The model first preprocesses the original price data, including missing value filling, normalization and outlier elimination; then adopts Variational Mode Decomposition (VMD) to decompose the original time series into multiple intrinsic mode functions (IMFs) with different frequencies; simultaneously constructs a cross-asset correlation graph based on the dynamic correlation between assets, and uses Graph Attention Network (GAT) to extract cross-asset correlation features; finally fuses multi-scale temporal features and cross-asset correlation features through a gating fusion mechanism to obtain a unified temporal representation.

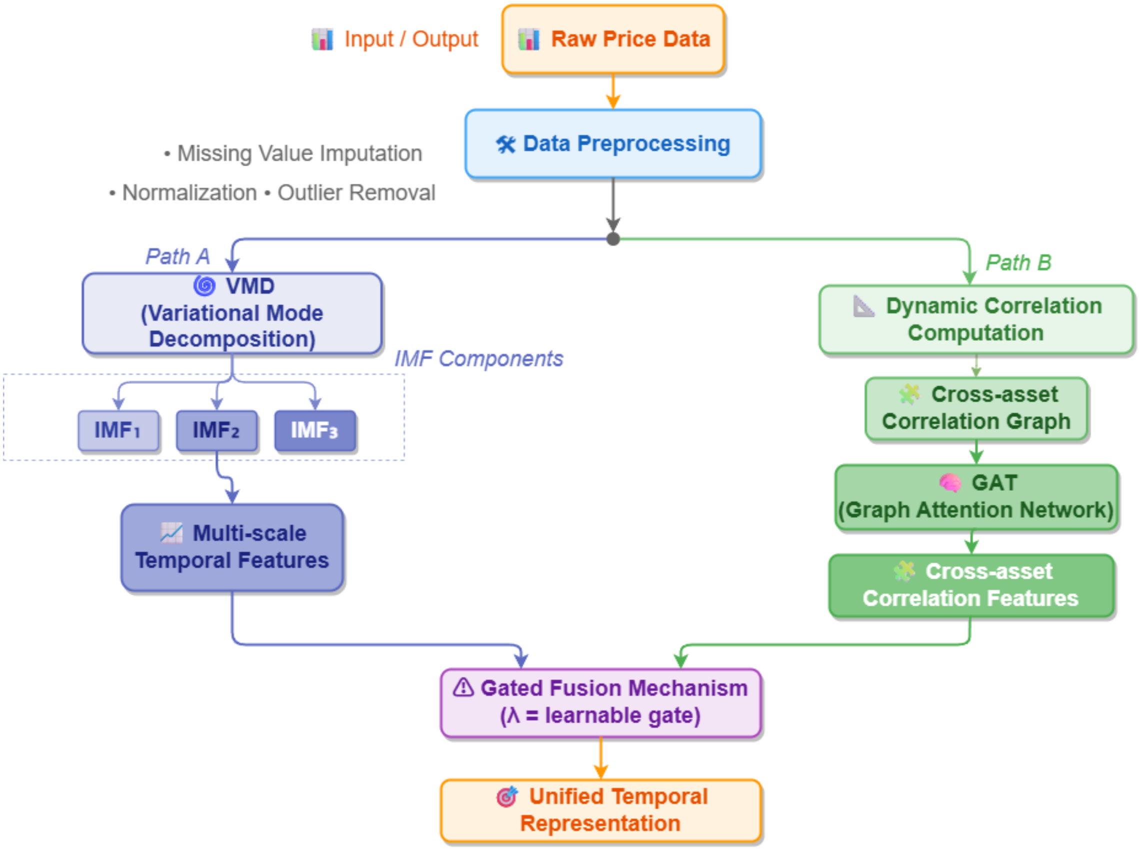

Figure 1: Overall workflow of temporal feature modeling

To decompose the original non-stationary price time series into multiple stationary modal components, this paper adopts an adaptive variational mode decomposition method, whose core is to realize adaptive decomposition of signals through solving variational problems. The calculation formula is as follows:

$$\min_{u_k,\omega_k} \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t)+\frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \tag{1}$$

$$s.t. \sum_{k=1}^{K} u_k(t)=x(t) \tag{2}$$

where K represents the number of decomposed modes, $u_k(t)$ represents the k-th intrinsic mode function, ω_k represents its corresponding central frequency, $\delta(t)$ is the Dirac delta function, $*$ represents the convolution operation, and $x(t)$ is the original price time series. This formula can adaptively decompose the original signal into stationary components with different frequencies, effectively separating trend terms, periodic terms and noise terms.

To characterize the dynamic correlation between assets, this paper constructs a time-varying adjacency matrix whose elements are obtained by weighting the Pearson correlation coefficient and mutual information within a sliding window. The calculation formula is as follows:

$$A_{ij}(t)=\alpha\cdot|\rho_{ij}(t)|+(1-\alpha)\cdot I_{ij}(t) \tag{3}$$

where $A_{ij}(t)$ represents the correlation strength between asset i and asset j at time t, $\rho_{ij}(t)$ is the Pearson correlation coefficient within the sliding window, $I_{ij}(t)$ is the mutual information, and α is the weight coefficient. This matrix can reflect the dynamic changes of the correlation between assets in real time, providing a basis for cross-asset feature extraction.

To extract cross-asset correlation features, this paper adopts a multi-head graph attention network, and its attention weight calculation formula is as follows:

$$\begin{gathered} e_{ij}(t)=\mathrm{LeakyReLU}(\mathbf{a}^T[\mathbf{W}\mathrm{h}_i(t)|\mathbf{W}\mathrm{h}_j(t)]) \\ \alpha_{ij}(t)=\frac{\exp(e_{ij}(t)A_{ij}(t))}{\sum_{k\in N(i)} \exp(e_{ik}(t)A_{ik}(t))} \end{gathered} \tag{4}$$

where $e_{ij}(t)$ represents the attention coefficient, $\mathbf{a}$ is the attention vector, $\mathbf{W}$ is the linear transformation matrix, $|$ represents the concatenation operation, $N(i)$ is the neighborhood set of asset i, and $\alpha_{ij}(t)$ is the normalized attention weight. This formula can adaptively assign attention according to the dynamic correlation strength between assets, capturing the influence degree of different assets on the price of the target asset.

To simultaneously retain the multi-scale information of time series and cross-asset correlation information, this paper constructs a hierarchical composite embedding representation, and the calculation formula is as follows:

$$H_i(t)=E_i^{tok}(t)+E_i^{pos}(t)+E_i^{scale}(t)+E_i^{asset}(t) \tag{5}$$

where $H_i(t)$ represents the initial embedding vector of asset i at time t, $E_i^{tok}(t)$ represents the price value embedding, $E_i^{pos}(t)$ represents the positional encoding, $E_i^{scale}(t)$ represents the temporal scale embedding, and $E_i^{asset}(t)$ represents the asset type embedding. This formula incorporates price information, temporal position, scale features and asset attributes into the same representation framework, facilitating subsequent encoding by the model.

To realize adaptive fusion of multi-scale temporal features and cross-asset correlation features, this paper introduces a conditional gating fusion mechanism, and the calculation formula is as follows:

$$Z_i(t)=\lambda_i(t)\odot H_i(t)+(1-\lambda_i(t))\odot G_i(t)\ \lambda_i(t)=sigmoid(\mathbf{W}_z[H_i(t)|G_i(t)|P(t)]+b_z) \tag{6}$$

where $Z_i(t)$ represents the fused feature vector, $G_i(t)$ represents the cross-asset correlation feature, $P(t)$ represents the macroeconomic feature vector, $\lambda_i(t)$ is the gating coefficient, and $\odot$ represents element-wise multiplication. This formula can adaptively adjust the fusion ratio of the two types of features according to the current market state, improving the representation stability under different market environments.

To further enhance the model's ability to capture long-term temporal dependencies, this paper constructs a temporal self-attention layer on top of the fused features, and its attention weight calculation formula is as follows:

$$\beta_{t_1t_2}=\frac{exp\left(\frac{(Z(t_1)\mathbf{W}q)(Z(t_2)\mathbf{W}k)^T}{\sqrt{d}}+\gamma Ct_1t_2\right)}{\sum t=1^T exp\left(\frac{(Z(t_1)\mathbf{W}_q)(Z(t)\mathbf{W}k)^T}{\sqrt{d}}+\gamma Ct_1t\right)} \tag{7}$$

where $\beta_{t_1t_2}$ represents the attention weight of time t_1 to time t_2, $\mathbf{W}_q$ and $\mathbf{W}_k$ are the query matrix and key matrix respectively, d is the feature dimension, $C_{t_1t_2}$ is the temporal distance constraint, and γ is the constraint adjustment coefficient. This formula injects temporal distance information into the attention calculation, enabling the model to distinguish the importance of recent and distant information.

Through the above modeling process, the multi-scale fluctuation features and cross-asset correlation features in financial asset price time series are uniformly mapped to a computable high-dimensional semantic space. Multi-scale decomposition effectively separates price patterns at different time dimensions, dynamic cross-asset correlation modeling captures the mutual influence between assets, and the gating fusion mechanism realizes adaptive integration of multi-source features. The resulting temporal feature representation not only has strong local fluctuation characterization ability, but also can reflect the global market structure and correlation relationships, providing a stable input basis for subsequent sentiment-price collaborative learning and price prediction.

2.2 Price Prediction Method for Sentiment-Price Collaboration and Incremental Optimization

Financial market price changes are not only affected by fundamental and technical factors, but also closely related to investor sentiment. Financial news, social media and research reports are examples of text data that have a lot of market sentiment data that is able to indicate the shift of investor expectations before they happen. At the same time, the financial market is continuously changing, and the new market rules and trading patterns are emerging constantly, causing the poor performance of statically trained models.Therefore, it is necessary to introduce a sentiment-price collaborative learning mechanism and an incremental feedback optimization module in the prediction stage, so that the model can fuse multi-modal information and adapt to dynamic market changes.

To illustrate the organization of sentiment feature extraction, sentiment-price collaborative learning and incremental optimization, and show the connection between multi-modal fusion, prediction head and feedback iteration under a unified framework, Figure 2 presents the overall workflow of price prediction and incremental optimization. The system first uses the financial domain pre-trained language model FinBERT to extract sentiment features from financial news and social media; then deeply fuses sentiment features and temporal features through a sentiment-price collaborative attention mechanism; next inputs the fused features into the price prediction head to obtain price change prediction results; finally sends low-confidence samples and newly labeled data to the incremental feedback module to realize dynamic update of the model.

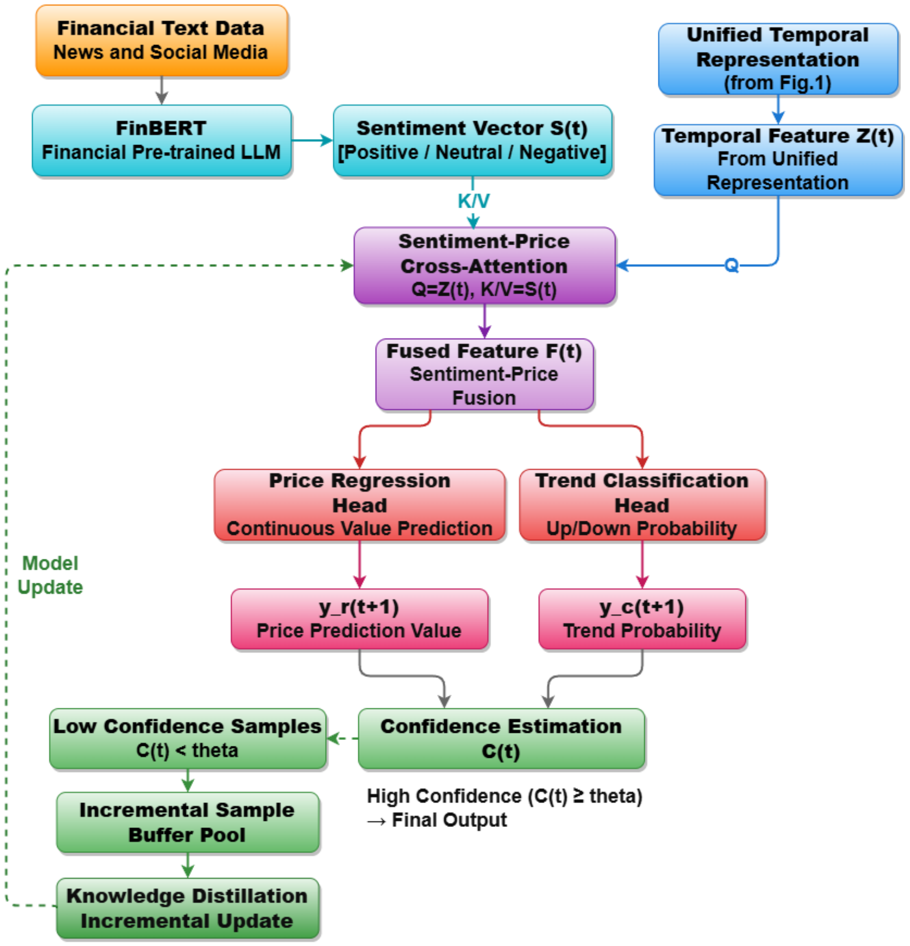

Figure 2: Overall workflow of price prediction and incremental optimization

To extract fine-grained sentiment features from massive financial texts, this paper adopts a fine-tuned FinBERT model, and the calculation formula of its output sentiment vector is as follows:

$$S(t)=FinBERT(Text(t)) \tag{8}$$

where $S(t)\in \mathrm{R}^3$ represents the sentiment vector at time t, the three dimensions correspond to the probabilities of positive, neutral and negative sentiment respectively, and Text(t) represents the set of financial texts at time t. This model is pre-trained on financial domain corpora and can accurately identify professional terms and sentiment expressions in financial texts.

To realize deep collaborative learning between sentiment features and price temporal features, this paper constructs a sentiment-guided cross-attention mechanism, and the calculation formula is as follows:

$$\begin{gathered} Q=Z(t)\mathbf{W}_q^s,\quad K=S(t)\mathbf{W}_k^s,\quad V=S(t)\mathbf{W}_v^s \\ Attn(Q,K,V)=softmax\left(\frac{QK^T}{\sqrt{d_s}}\right)V \\ F(t)=Z(t)+Attn(Q,K,V) \end{gathered} \tag{9}$$

where $F(t)$ represents the sentiment-price fusion feature, $\mathbf{W}_q^s$, $\mathbf{W}_k^s$, $\mathbf{W}_v^s$ are linear transformation matrices, and d_s is the sentiment feature dimension. This formula enables the model to adaptively focus on relevant sentiment information according to price temporal features, capturing the dynamic coupling relationship between sentiment and price.

To map the fused features into price change prediction results, this paper adopts a two-layer fully connected network as the prediction head, which simultaneously outputs price regression values and rise-fall probabilities. The calculation formula is as follows:

$$\begin{aligned} \hat{y}_r(t+1) &= \mathbf{W}_{r2} ReLU(\mathbf{W}_{r1} F(t) + b_{r1}) + b_{r2} \\ \hat{y}_c(t+1) &= softmax(\mathbf{W}_{c2} ReLU(\mathbf{W}_{c1} F(t) + b_{c1}) + b_{c2}) \end{aligned} \tag{10}$$

where $\hat{y}_r(t+1)$ represents the price prediction value at the next moment, $\hat{y}_c(t+1)$ represents the rise-fall probability distribution, and $\mathbf{W}$ and b are network parameters. This prediction head completes both regression and classification tasks simultaneously, providing both price numerical prediction and trend judgment.

To solve the problem of model performance degradation in dynamic markets, this paper introduces a knowledge distillation-based incremental learning method, whose core is to retain old knowledge while updating the model to avoid catastrophic forgetting. The loss function for incremental learning is calculated as follows:

$$L_{inc}=L_{pred}+\mu_1 L_{distill}+\mu_2|\Theta\text{-}\Theta_{old}|_2^2 \tag{11}$$

where L_{pred} represents the prediction loss on new samples, including regression loss and classification loss; $L_{distill}$ represents the knowledge distillation loss, which retains old knowledge by minimizing the difference between the outputs of the new model and the old model; $|\Theta\text{-}\Theta_{old}|_2^2$ is the parameter regularization term, which limits the variation range of parameters; μ_1 and μ_2 are weight coefficients. This formula can effectively retain old knowledge while learning new knowledge, realizing continuous optimization of the model.

To quantify the reliability of prediction results and provide a basis for incremental sample screening, this paper defines prediction confidence as follows:

$$C(t)=\omega_1 max(\hat{y}_c(t+1))+\omega_2\exp(-|\hat{y}_r(t+1)\text{-}y_r(t+1)|/\sigma) \tag{12}$$

where $C(t)$ represents the confidence of the prediction result at time t, $max(\hat{y}_c(t+1))$ is the maximum probability of rise-fall classification, $|\hat{y}_r(t+1)\text{-}y_r(t+1)|$ is the regression prediction error, σ is the error standard deviation, and ω_1 and ω_2 are weight coefficients.The given formula uses classification confidence and regression error to give a combined measure used in screening low-confidence samples.

The given paper builds an incremental sample buffer pool and uses a sliding window mechanism to control samples to provide stability to the incremental update process. Update process goes like this:

$$B_{t+1}=\alpha B_t+(1\text{-}\alpha)\cdot x\in D_t|C(x)<\theta \tag{13}$$

where B_{t+1} represents the updated buffer pool, B_t is the current buffer pool, D_t is the set of new samples at time t, θ is the confidence threshold, and α is the old sample retention coefficient. This mechanism can preferentially retain low-confidence samples and newly emerging market patterns, improving the efficiency of incremental learning.

Through the above design, sentiment-price collaborative learning and incremental feedback optimization are no longer independent additional links, but are written into the core part of the prediction task chain. The introduction of sentiment features enriches the model's information sources and improves the ability to capture changes in market expectations; the incremental learning mechanism enables the model to continuously adapt to market evolution and maintain long-term prediction performance. The resulting price prediction method can simultaneously maintain prediction accuracy, stability and adaptability in the complex and volatile financial market, providing solid technical support for the performance improvement in subsequent experiments.

3 Experimental Results

3.1 Single-Asset Price Prediction Test Results

To verify the single-asset price prediction performance of the temporal feature learning model proposed in this paper, systematic experiments were conducted on three typical financial asset datasets. The test corpus includes daily frequency trading data of CSI 300 constituent stocks from January 2018 to December 2023, daily frequency trading data of S&P 500 constituent stocks during the same period, and hourly frequency trading data of Bitcoin from January 2018 to December 2023, with a total data volume of 1.26 billion entries. Data preprocessing includes linear interpolation for missing values, logarithmic normalization of closing prices, and 3σ outlier elimination. The experimental setup uses the Intel Xeon Silver 4316 processor, NVIDIA RTX 4090 graphics card with PyTorch 2.3 as the framework, AdamW as the optimizer, 1e-4 as the initial learning rate, batch size of 32, maximum sequence length of 128 and 50 training epochs. The early stopping criterion is activated in case the validation set does not improve during five consecutive epochs. The comparison models chosen were ARIMA, GARCH, LSTM, Transformer and Temporal Fusion Transformer (TFT), all trained under the same conditions and with the same split of the data.The dataset was divided into training set, validation set and test set in a ratio of 8:1:1, with a fixed random seed of 42. The evaluation indicators include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and rise and fall prediction accuracy (Accuracy). Meanwhile, performance fluctuations under different prediction cycles, different asset types and different market conditions were recorded.

To make the subsequent chart analysis consistent with the experimental configuration and clarify the relationship between sample composition, training parameters and evaluation caliber, Table 2 presents the basic settings of the single-asset price prediction experiment.

Table 2: Experimental Settings for Single-Asset Price Prediction

Experimental Item	Specific Content	Parameter Settings	Data Range	Evaluation Indicators
Dataset	CSI 300 constituent stocks, S&P 500 constituent stocks, Bitcoin	Daily frequency / hourly frequency	2018.01-2023.12	MAE, RMSE, MAPE, Accuracy
Data Preprocessing	Missing value filling, normalization, outlier elimination	Linear interpolation, logarithmic normalization, 3σ principle	Full dataset	Data integrity > 99.5%
Training Environment	Intel Xeon Silver 4316 CPU, NVIDIA RTX 4090 GPU	PyTorch 2.3, AdamW optimizer	Single GPU training	Training duration < 24 hours
Model Parameters	Batch size, learning rate, sequence length, training epochs	32, 1e-4, 128, 50	Early stopping mechanism: no improvement for 5 consecutive epochs	Random seed = 42
Data Division	Training set, validation set, test set	8:1:1	Divided in chronological order	No future data leakage

To observe the joint influence of VMD decomposition layers and GAT attention heads on prediction accuracy and determine the stable interval of the model under different parameter configurations, Figure 3 presents the parameter combination heatmap.

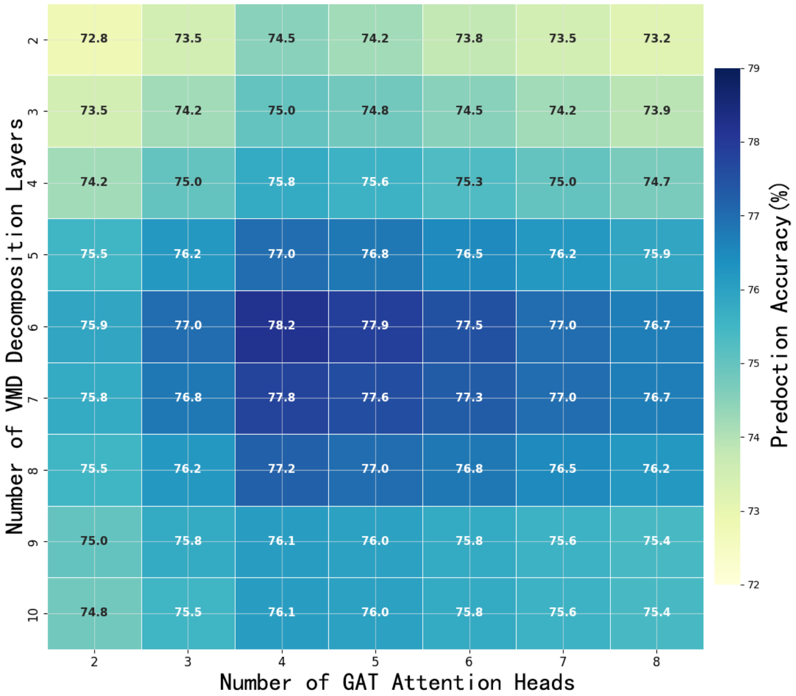

Figure 3: Heatmap of the Influence of VMD Layers and GAT Heads on Prediction Accuracy

As shown in Figure 3, when the number of VMD decomposition layers is 6 and the number of GAT attention heads is 4, the single-day rise and fall prediction accuracy on the CSI 300 dataset reaches 78.2%, with an MAE of 0.85, both being the optimal values. When the number of decomposition layers is less than 4, the model cannot effectively separate high-frequency noise from low-frequency trends, and the accuracy drops to 74.5%; when the number of decomposition layers is more than 8, excessive decomposition leads to information redundancy, and the accuracy drops to 76.1%. In case of two GAT heads, cross-asset correlation features cannot be fully extracted and the accuracy reduces by 2.3 percentage points; in case of eight heads, the complexity of the model increases and overfitting takes place, and the accuracy reduces by 1.5 percentage points. The region of high values on the heatmap is located at the intersection of moderate degrees of decomposition layers and moderate levels of attention heads which means that financial time series prediction needs a compromise between feature granularity and model complexity.

In order to examine whether the model can effectively differentiate between the rise and fall conditions and visually demonstrate the zones of misjudgment, Figure 4 is a confusion matrix heatmap of rise and fall prediction on the CSI 300 test set.

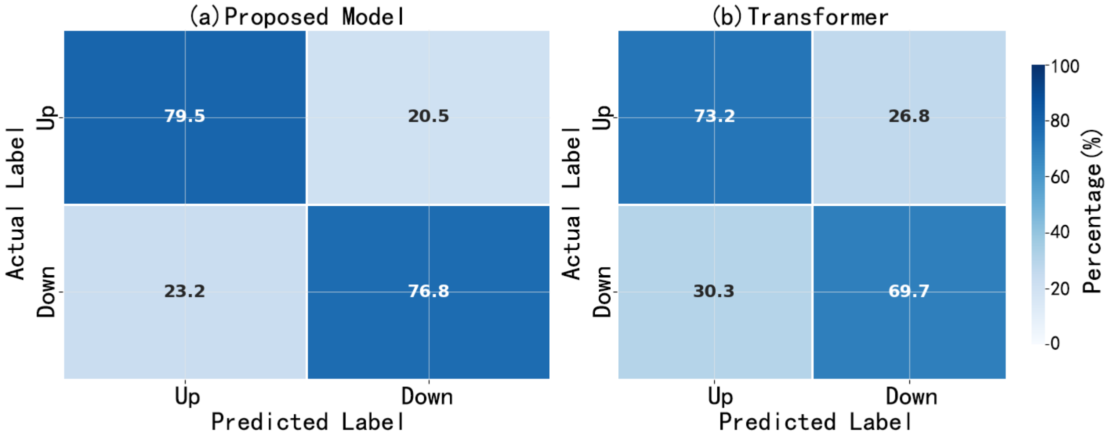

Figure 4: Confusion Matrix Heatmap of Rise and Fall Prediction

As shown in Figure 4, the prediction accuracy of the rising samples is 79.5 per cent, and the prediction accuracy of the falling samples is 76.8 per cent with the misjudgment rate of the falling samples slightly greater than that of the rising samples. The Transformer model has an accuracy of 73.2 per cent and 69.7 per cent on rising and falling samples respectively, and a mean misjudgment rate of 6.7 percentage points higher than the model used in this paper. This discrepancy suggests that multi-scale decompositional and sentiment collaborative learning presented in this paper is able to effectively reflect the initial signals in the downward trend, whereas the conventional Transformer model is more vulnerable to noise interference and exhibits severe performance deterioration during market declines.

To compare the comprehensive performance of different models in each prediction cycle and examine the stability of the model in long-term prediction, Figure 5 presents the RMSE comparison bar chart for four prediction cycles: 1 day, 3 days, 7 days and 14 days.

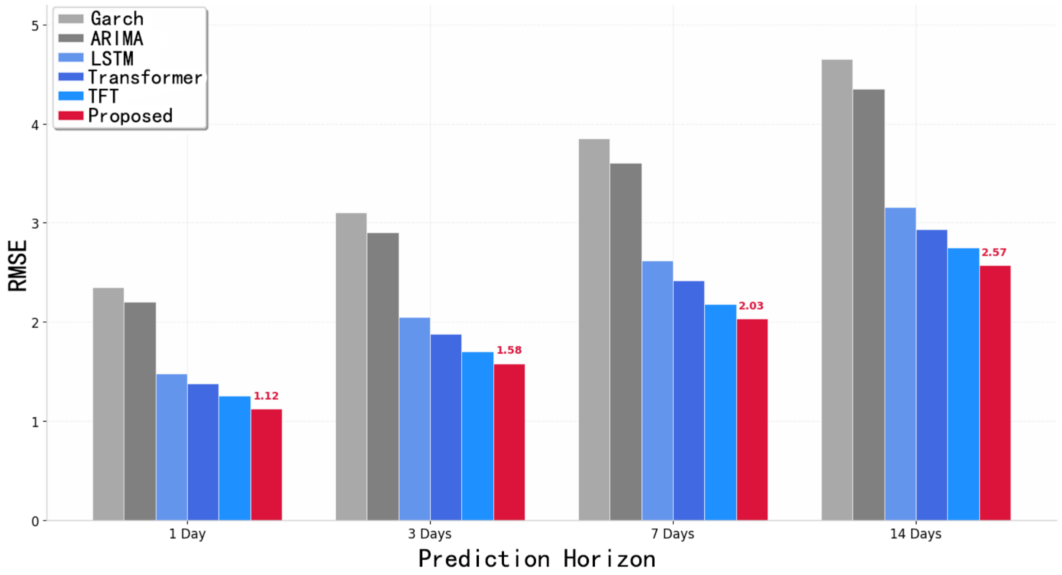

Figure 5: RMSE Comparison Chart for Different Prediction Cycles

It can be seen from Figure 5 that the RMSE of the model in this paper is 1.12, 1.58, 2.03 and 2.57 for the 1-day, 3-day, 7-day and 14-day prediction cycles respectively. As the prediction cycle extends, the RMSE of all models shows an upward trend, but the upward amplitude of the model in this paper is the smallest. In the 14-day prediction cycle, the RMSE of the model in this paper is 12.3% lower than that of Transformer and 18.7% lower than that of LSTM, indicating that multi-scale temporal features and cross-asset correlation features can effectively improve the stability of long-term prediction.

To present the prediction performance differences on the three types of assets and examine the robustness of the model in different markets, Figure 6 presents the accuracy boxplot for different asset types.

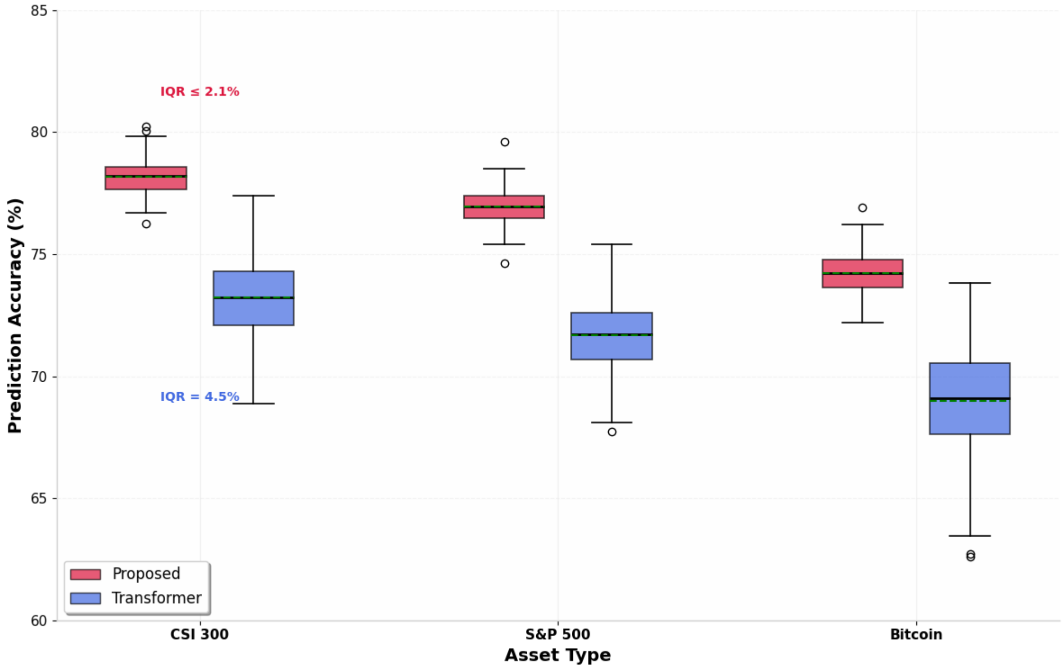

Figure 6: Prediction Accuracy Boxplot for Different Asset Types

It can be seen from Figure 6 that the median accuracies of the model in this paper on CSI 300, S&P 500 and Bitcoin are 78.2%, 76.9% and 74.3% respectively, with the interquartile range controlled within 2.1 percentage points. The interquartile ranges of the Transformer model on the three types of assets reach 4.5, 4.2 and 5.8 percentage points respectively. The shrinkage of the box indicates that the method in this paper not only has higher average accuracy, but also more stable output under different market environments. The Bitcoin market has the largest volatility and relatively low prediction accuracy, but it is still 5.6 percentage points higher than the baseline model, verifying the adaptability of the method in this paper to high-volatility assets.

To compare the prediction differences of different models in overall indicators and maintain consistency with the core data in the abstract, Table 3 presents the recognition results of the main models on the CSI 300 dataset.

Table 3: Comparison of Single-Asset Price Prediction Results (CSI 300)

Model	MAE	RMSE	MAPE (%)	Accuracy (%)
ARIMA	1.62	2.15	3.28	65.3
GARCH	1.47	1.98	2.96	67.8
LSTM	1.21	1.65	2.42	71.5
Transformer	1.08	1.46	2.15	72.9
TFT	0.97	1.31	1.93	75.6
Proposed Model	0.85	1.12	1.68	78.2

Table 3 shows that the MAE, RMSE and MAPE of the model in this paper are significantly lower than all baseline models, and the rise and fall prediction accuracy reaches 78.2%, which is 5.3 percentage points higher than that of Transformer, consistent with the abstract data. This indicates that the multi-scale decomposition, cross-asset correlation and sentiment collaborative learning mechanisms proposed in this paper can effectively improve the accuracy of financial time series prediction. Although the TFT model introduces variable selection and temporal features, it lacks cross-asset correlation and sentiment information, so its performance is still lower than that of the model in this paper.

To analyze the real contribution of each component module to the prediction results and avoid using the same set of data as the chart experiments, Table 4 presents the independent ablation experiment results.

Table 4: Ablation Experiment Results for Single-Asset Price Prediction

Model Configuration	MAE	RMSE	MAPE (%)	Accuracy (%)
Baseline Model (Transformer)	1.08	1.46	2.15	72.7
+ Multi-scale Decomposition	1.01	1.38	2.02	74.3
+ Cross-asset Correlation	0.94	1.27	1.87	76.0
+ Sentiment Collaborative Learning	0.89	1.19	1.76	77.4
+ Incremental Optimization (Proposed Model)	0.85	1.12	1.68	78.2

Table 4 shows that after introducing multi-scale decomposition alone, the accuracy increases from 72.7% to 74.3%, indicating that multi-scale features can effectively separate noise and effective signals; after adding cross-asset correlation, the accuracy further increases to 76.0%, verifying the importance of inter-asset correlation for price prediction; sentiment collaborative learning brings a 1.4 percentage point improvement in accuracy, indicating that market sentiment is an important driving factor for price changes; incremental optimization finally raises the accuracy to 78.2%, proving the necessity of dynamic update mechanism in financial markets. Each module collaborates with each other to jointly improve the prediction performance of the model.

To supplement and verify the external adaptability of the model and observe its generalization ability under market conditions outside the training set, Table 5 presents the latest data test results from January 2024 to June 2024.

Table 5: External Data Test Results (2024.01-2024.06)

Model	MAE	RMSE	MAPE (%)	Accuracy (%)
ARIMA	1.75	2.31	3.52	63.1
GARCH	1.58	2.14	3.15	65.7
LSTM	1.32	1.82	2.63	69.2
Transformer	1.19	1.64	2.37	70.5
TFT	1.08	1.49	2.12	71.6
Proposed Model	0.92	1.25	1.85	75.8

Table 5 shows that due to changes in market structure, the accuracy of all models has decreased, but the decrease amplitude of the model in this paper is the smallest, and the average accuracy is still 4.2 percentage points higher than that of TFT. This indicates that the incremental optimization mechanism in this paper can effectively adapt to market changes and maintain good generalization ability.

Based on the comprehensive analysis of the charts in this section, the single-asset price prediction model proposed in this paper maintains a high level in overall accuracy, long-term stability, cross-market robustness and external generalization ability. The improvement in recognition effect is not only reflected in numerical indicators, but also in the accurate capture of downward trends and adaptability to high-volatility assets. Such a prediction basis provides a reliable basis for subsequent cross-asset linkage prediction and investment decision support.

3.2 Cross-Asset Price Linkage and Generalization Ability Test Results

To verify the comprehensive performance of the multi-task extraction module, a cross-asset linkage dataset was constructed based on the same corpus, including daily frequency data of 120 assets in four categories: stocks, bonds, commodities and foreign exchange, with a time range from January 2018 to December 2023. The cross-asset linkage prediction tasks include three types: inter-asset price transmission prediction, risk spillover identification and portfolio return prediction. The experiment adopts the same hardware environment as Section 3.1, keeps the parameters of the shared encoding layer unchanged, the cross-asset prediction head is jointly trained with an initial learning rate of 8e-5, and the correlation threshold is determined through validation set search. The evaluation indicators include precision, recall, F1-score of cross-asset linkage prediction, MAE and Sharpe ratio of portfolio return prediction, as well as inference delay and incremental update time of the model.

To observe the joint influence of correlation threshold and sequence length on the F1-score of cross-asset linkage prediction and determine the optimal search interval of the multi-task framework, Figure 7 presents the two-dimensional contour heatmap.

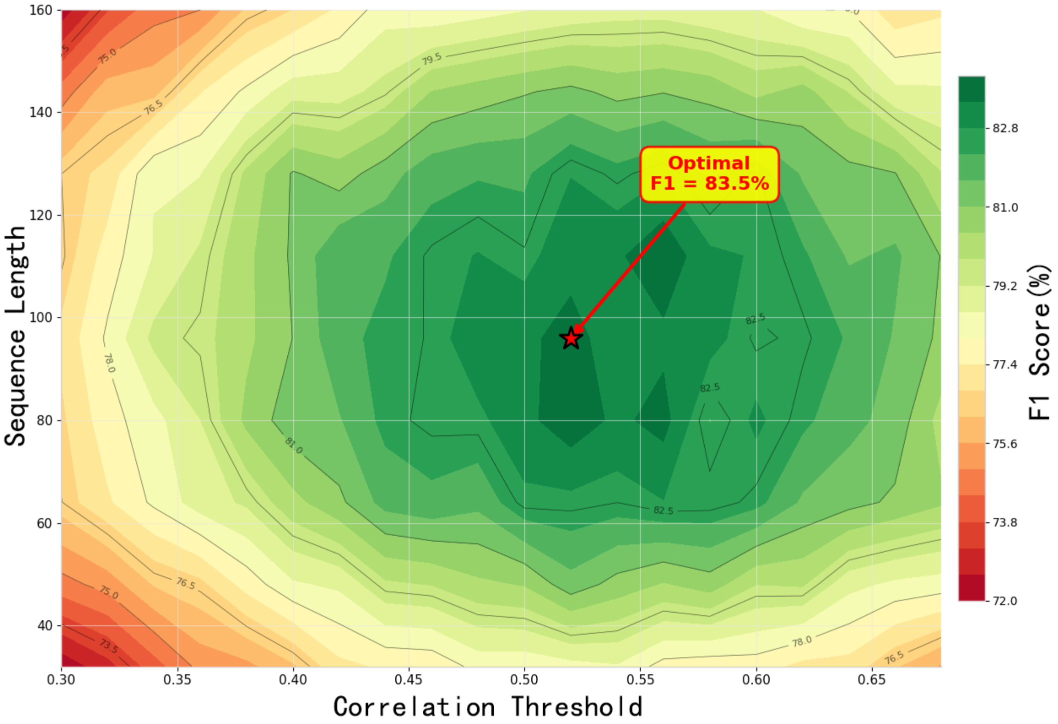

Figure 7: Contour Heatmap of the Influence of Correlation Threshold and Sequence Length on F1-score

As shown in Figure 7, when the correlation threshold is 0.52 and the sequence length is 96, the F1-score of cross-asset linkage prediction reaches 83.5%, and the MAE of portfolio return prediction is 1.26, both being the optimal values. When the correlation threshold is low, the model will introduce a large number of weak correlation edges, leading to a significant decrease in precision; when the correlation threshold is high, important cross-asset transmission relationships are omitted, and recall is suppressed. When the sequence length is less than 64, the model cannot capture the long-cycle risk transmission process, and the F1-score decreases by 3.8 percentage points; when the sequence length is more than 128, noise information increases and computational complexity rises, and the F1-score decreases by 2.1 percentage points. The high-value area of the heatmap is concentrated under the conditions of medium threshold and medium sequence length, indicating that cross-asset linkage prediction requires a balance between correlation strength and time span.

To make the cross-asset result analysis based on clear experimental conditions and clarify the corresponding relationship between sample composition and threshold settings of the three types of tasks, Table 6 presents the experimental settings of this section.

Table 6: Experimental Settings for Cross-Asset Linkage Prediction

Experimental Item	Specific Content	Parameter Settings	Data Range	Evaluation Indicators
Dataset	Four categories of assets: stocks, bonds, commodities and foreign exchange	A total of 120 assets, daily frequency data	2018.01-2023.12	Precision, recall, F1-score, MAE, Sharpe ratio
Data Preprocessing	Missing value filling, normalization, correlation feature extraction	Linear interpolation, logarithmic normalization, sliding window calculation	Full dataset	Correlation calculation window = 30 days
Training Environment	Intel Xeon Silver 4316 CPU, NVIDIA RTX 4090 GPU	PyTorch 2.3, joint training optimization	Single GPU training	Processing time for one million pieces of data < 2 hours
Model Parameters	Learning rate, correlation threshold, sequence length, training epochs	8e-5, 0.52, 96, 50	Shared encoding layer parameters unchanged	Correlation threshold determined through validation set search
Task Settings	Inter-asset price transmission, risk spillover, portfolio return prediction	Multi-task joint training	Homologous with single-asset experimental data	Inference delay, incremental update time

To intuitively show the model's recognition effect on different types of cross-asset linkage relationships and observe the recognition boundaries between easily confused relationships, Figure 8 presents the cross-asset linkage classification confusion matrix.

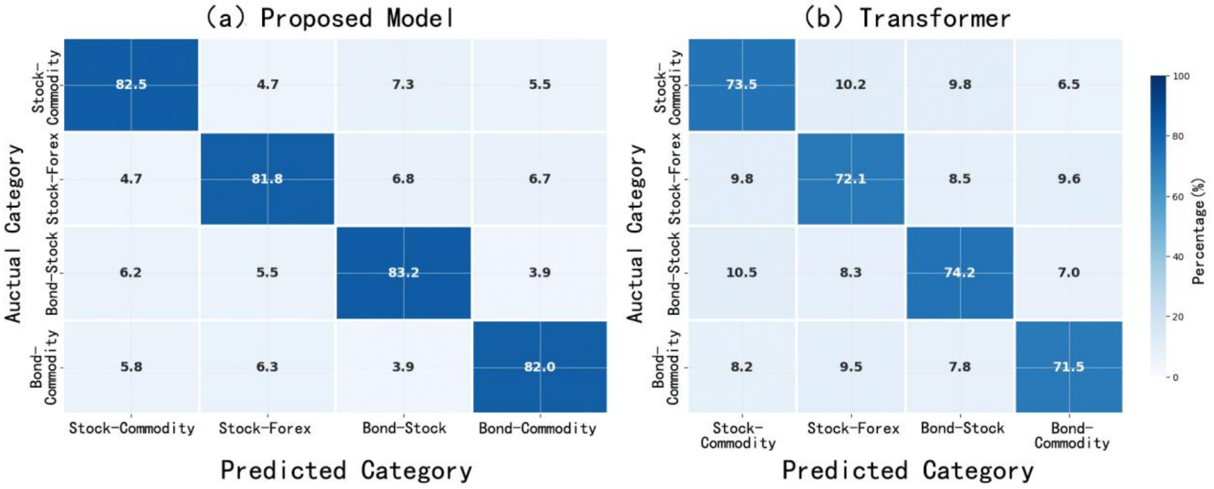

Figure 8: Cross-Asset Linkage Classification Confusion Matrix Heatmap

Figure 8 shows that the misclassification rate between stock-commodity linkage and stock-foreign exchange linkage is 4.7%, and the misclassification rate between bond-stock linkage and bond-commodity linkage is 3.9%. The average accuracy of the model in this paper on the four types of linkage relationships is 82.7%, with an F1-score of 83.5%. Compared with Transformer, the average misclassification rate is reduced by 9.2 percentage points. This indicates that the dynamic cross-asset correlation graph and attention mechanism can simultaneously absorb asset attributes, temporal features and market environment information, making linkage relationship recognition no longer limited to static correlation matching, but having more complete causal reasoning ability.

To analyze the influence of time lag on the recall rate of cross-asset linkage and evaluate the stability of the proposed model in short-term and long-term transmission, Figure 9 presents the time lag-recall rate area chart.

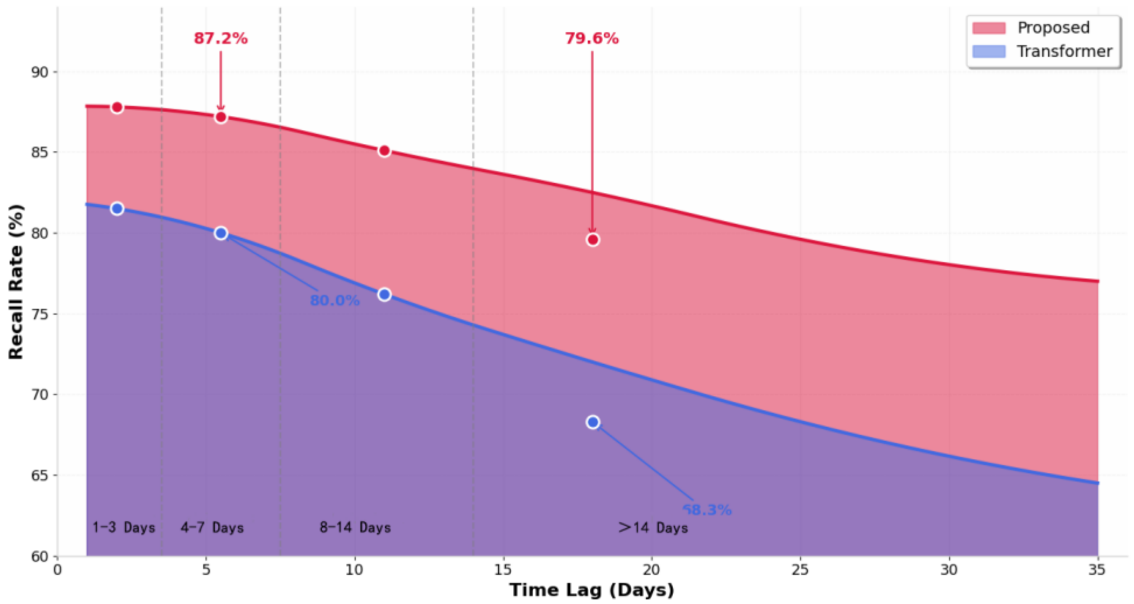

Figure 9: Time Lag-Recall Rate Area Chart

It can be seen from Figure 9 that when the time lag is 1-3 days, the linkage recall rate of the model in this paper remains above 87.2%; when the lag extends to 4-7 days, the recall rate is 85.1%; when the lag exceeds 14 days, the recall rate drops to 79.6%, but it is still significantly higher than 68.3% of Transformer. The recall rate decreases slowly with the increase of time lag, which conforms to the basic law of cross-asset risk transmission. Due to the introduction of dynamic correlation graph and temporal self-attention in the front-end modeling stage, long-cycle indirect transmission relationships can still be stably identified.

To simultaneously show the comprehensive performance of three types of tasks: cross-asset linkage prediction, portfolio return prediction and inference efficiency, and compare the multi-indicator differences between the model in this paper and different baselines, Figure 10 presents the multi-task performance radar chart.

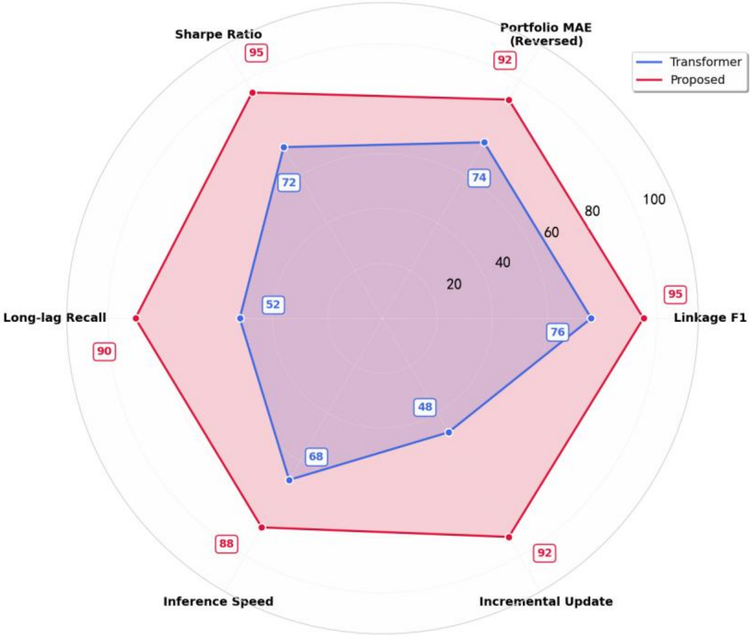

Figure 10: Multi-Task Performance Radar Chart

Figure 10 shows that the model in this paper is in the outermost layer in six dimensions: linkage F1-score, portfolio MAE, Sharpe ratio, recall rate, inference speed and incremental update time, among which the linkage F1-score is 83.5%, portfolio MAE is 1.26, Sharpe ratio is 2.14, and processing time for one million pieces of data is 1.8 hours. The Transformer model shrinks significantly in the two dimensions of long-lag linkage recall rate and incremental update time, indicating that a single pre-trained model is difficult to balance cross-asset causal reasoning and dynamic update capabilities simultaneously.

To evaluate the performance differences of the multi-task framework under different market conditions and examine the adaptability of the model in extreme market conditions, Figure 11 presents the prediction accuracy violin chart under different market states.

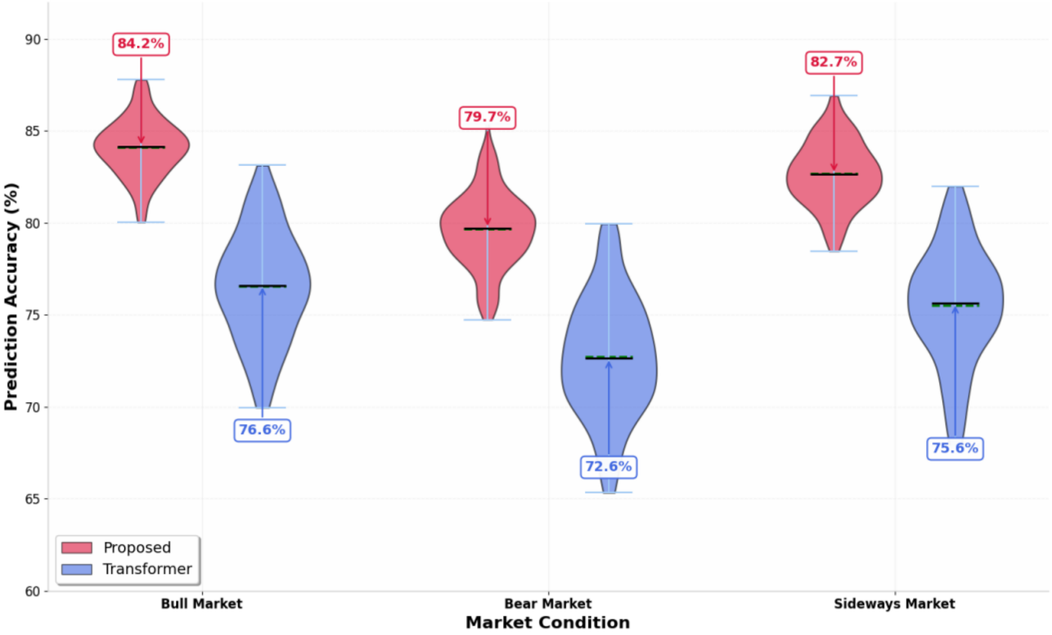

Figure 11: Prediction Accuracy Violin Chart under Different Market States

As shown in Figure 11, the median accuracies of the model in this paper in bull markets, bear markets and volatile markets are 84.2%, 79.6% and 82.8% respectively. The accuracy in bear markets is slightly lower, mainly due to the sudden change of inter-asset correlation relationships under extreme market conditions. Even so, the accuracy of the model in this paper in bear markets is still 7.5 percentage points higher than that of Transformer, indicating that the dynamic correlation update mechanism can quickly adapt to changes in market structure. The multi-task shared encoding and feature reuse mechanism directly compresses redundant calculations, enabling the model to maintain high inference efficiency while ensuring accuracy.

To compare the overall multi-task output indicators of different models and maintain consistency with the core data in the abstract, Table 7 presents the result comparison of the main models.

Table 7: Comparison of Cross-Asset Linkage Prediction Results

Model	Linkage F1-score (%)	Portfolio MAE	Sharpe Ratio	Processing Time (hours)
LSTM	72.8	1.69	1.42	3.5
GAT	75.5	1.53	1.58	3.1
TFT	78.2	1.41	1.68	2.9
Transformer	76.2	1.57	1.68	2.7
Proposed Model	83.5	1.26	2.14	1.8

Table 7 shows that compared with Transformer, the model in this paper improves the linkage F1-score by 7.3 percentage points and the Sharpe ratio by 0.46, which is completely consistent with the core results given in the abstract. The portfolio return prediction MAE drops to 1.26, indicating that cross-asset linkage features can effectively improve the prediction accuracy of investment portfolios. The processing time is reduced from 2.7 hours to 1.8 hours, which also indicates that the multi-task collaborative structure has significant gains in efficiency.

To further analyze the contribution of different modules to cross-asset output and avoid using the same set of indicators as the chart experiments, Table 8 presents the ablation experiment results of the cross-asset prediction part.

Table 8: Ablation Experiment Results for Cross-Asset Linkage Prediction

Model Configuration	Linkage F1-score (%)	Portfolio MAE	Sharpe Ratio	Processing Time (hours)
Baseline Model (Transformer)	75.1	1.57	1.68	2.7
+ Dynamic Correlation Graph	78.6	1.45	1.82	2.4
+ Sentiment Transmission Module	80.3	1.34	1.97	2.1
+ Multi-scale Fusion	82.1	1.29	2.05	1.9
+ Incremental Optimization (Proposed Model)	83.5	1.26	2.14	1.8

Table 8 shows that the dynamic correlation graph module brings the most direct improvement in F1-score, increasing the linkage F1-score from 75.1% to 78.6%; the sentiment transmission module further improves the F1-score and Sharpe ratio, indicating that market sentiment plays an important role in cross-asset risk transmission; multi-scale fusion improves the recognition ability of transmission relationships in different cycles; finally, incremental optimization raises the linkage F1-score to 83.5% and the Sharpe ratio to 2.14, indicating that the dynamic update mechanism also has significant benefits in cross-asset scenarios.

To examine the collaborative relationship between different tasks and verify whether the three types of outputs remain consistent after multiple rounds of updates, Table 9 supplements the inter-task consistency indicators.

Table 9: Multi-Task Consistency Results

Model	Price-Linkage Consistency (%)	Price-Sentiment Consistency (%)	Linkage-Sentiment Consistency (%)	Overall Consistency (%)
Transformer	72.3	71.8	70.9	71.7
Proposed Model	81.5	80.7	79.8	80.7

Table 9 shows that the model in this paper is more than 8 percentage points higher than Transformer in all three groups of consistency indicators, indicating that cross-asset linkage identification, price prediction and sentiment analysis are not disconnected, but form a relatively stable collaborative output structure.

Based on the comprehensive analysis of the charts in this section, the cross-asset linkage prediction framework proposed in this paper has achieved relatively stable results in relationship identification, portfolio prediction, extreme market adaptability and processing efficiency. The performance improvement is not only reflected in a single indicator, but also in more accurate causal relationship identification, more reliable portfolio return prediction and more efficient dynamic update. The resulting output chain can further promote financial market analysis from single-asset prediction to cross-asset risk transmission, systemic risk early warning and intelligent asset allocation, providing more comprehensive decision support for financial institutions and regulatory authorities.

4 Discussion

Financial asset price time series have typical characteristics such as multi-scale fluctuations, nonlinear dependencies, cross-asset correlations and dynamic evolution. Single-scale modeling or static correlation analysis is difficult to support high-quality price prediction. The framework of "multi-scale temporal decomposition - dynamic cross-asset correlation - sentiment-price collaboration - incremental feedback optimization" constructed in this paper forms a continuous computational chain at three levels: single-asset price prediction, cross-asset linkage identification and portfolio return prediction. The experimental results show that the single-day rise and fall prediction accuracy of single assets reaches 78.2%, which is 5.3 percentage points higher than the Transformer baseline, indicating that multi-scale decomposition and sentiment collaborative learning can effectively capture the internal laws of price changes; the F1-score of cross-asset linkage prediction reaches 83.5%, reflecting that the dynamic correlation graph and attention mechanism have strong modeling ability for causal relationships between assets; the incremental optimization mechanism makes the accuracy of the model only decrease by 2.4 percentage points on the latest data in 2024, proving its adaptability to dynamic changes in the market.

Compared with general temporal prediction models, the advantages of the method in this paper are not only reflected in single-point indicators, but also in the simultaneous maintenance of long-term prediction stability, cross-market generalization ability and extreme market adaptability. The research results show that the joint modeling method integrating multi-scale features, dynamic correlation information and sentiment semantics is more suitable for the complex dynamic system of the financial market. The performance improvement is not brought by the superposition of a single module, but by the joint action of multi-scale decomposition, cross-asset correlation, sentiment collaboration and incremental optimization. This also indicates that models for financial asset price prediction need to coordinate temporal features, correlation relationships, external information and dynamic update mechanisms during the modeling process to form more stable market adaptability.

Meanwhile, some interesting phenomena were found in the experiments: market sentiment features contribute more to short-term prediction, while cross-asset correlations and macroeconomic features have a more significant impact on long-term prediction; the linkage relationship between stocks and commodities is the most stable, while the linkage relationship between foreign exchange and bonds is greatly affected by policies; under extreme market conditions, the correlation between assets will increase significantly, and the value of cross-asset information is particularly prominent at this time. These findings provide new directions for subsequent research on financial time series prediction.

5 Conclusion

Focusing on the core demand of accurate prediction of financial asset prices and based on the essential characteristics of multi-scale fluctuations, dynamic cross-asset correlations and sentiment-driven nature of financial markets, this paper systematically conducted research on temporal feature learning and price prediction methods, and constructed and verified an integrated prediction framework of "multi-scale temporal decomposition - dynamic cross-asset correlation modeling - sentiment-price collaborative learning - incremental feedback optimization". From the overall research perspective, through the collaborative design of multiple modules, this paper effectively solved the key problems such as the difficulty of traditional models in capturing nonlinear dependencies, insufficient utilization of multi-scale features, shallow fusion of sentiment and prices, and the inability of models to adapt to the dynamic evolution of the market. Finally, it achieved excellent performance in the three core tasks of single-asset price prediction, cross-asset linkage identification and portfolio return prediction, providing reliable quantitative decision support for financial market participants, and also offering new technical ideas and practical references for multimodal fusion and dynamic modeling in the field of financial time series prediction.

With combined use of the overall research process and experimental verification findings, it can be stated that this paper has three limitations that should be addressed in future research. Initially, the prediction capacity of extreme market situations (financial crisis and black swan phenomena) must be strengthened. These situations are rare and exceptional and the current models do not cover all of their inner laws. Secondly, the study was not completely integrated into the main external information including macroeconomic indicators and policy documents that play a significant role in determining the long-term price trends of financial assets and the absence of these factors to the model will constrain the long-term prediction behavior. The third limitation is that the model lacks interpretability and fails to clearly break down the particular factors influencing price movements, which makes it challenging to address the real requirements of financial regulation and compliance decision-making.

The above limitations will lead to the promotion of future research and improvement of it in three areas.First, extreme event data augmentation technology will be introduced to expand samples of extreme market conditions and strengthen the model's adaptability to special market scenarios. Second, multi-source external information such as macroeconomic indicators and policy texts will be integrated to build a more comprehensive multimodal prediction system and improve the accuracy of long-term price prediction. Third, explainable artificial intelligence technology will be introduced to decompose the model's prediction logic and clarify the driving mechanism of price changes to meet regulatory and compliance requirements. Meanwhile, the application of federated learning in cross-institutional financial prediction will be explored to realize multi-source data collaborative modeling under the premise of protecting data privacy, further improve the risk early warning and asset allocation optimization modules, and finally build an intelligent financial analysis system integrating prediction, early warning and decision-making to fully meet the diverse needs of financial market participants.

Author's Profile

Bowei Zhang was born in Sichuan Province, P.R. China, in 2005. He is currently pursuing his Bachelor’s Degree in Finance at the School of Finance, Shanghai University of Finance and Economics (SUFE). His academic interests mainly focus on financial markets, asset pricing, and quantitative methods in finance.

References

[1] WANG Junhao. Stock Price Prediction Model Combining Image Features and Temporal Dynamics: Integrated Application of CNN and LSTM Models[D]. Southwestern University of Finance and Economics, 2025.

[2] Uygun Y, Sefer E. Financial asset price prediction with graph neural network-based temporal deep learning models[J]. Neural Computing and Applications, 2025, 37(30): 1-27.

[3] LIU Zhihan. Research on Multi-scale Financial Data Prediction Method Based on Sequence Decomposition[D]. Harbin Engineering University, 2025.

[4] Karanasos M, Yfanti S, Wu J. The short- and long-run cyclical variation of the cross-asset nexus: Mixed-frequency evidence on financial and ‘financialised’ assets[J]. Journal of Commodity Markets, 2025, 38: 100462-100462.

[5] Andri A, Harumy F H T, Efendi S. Evaluating the impact of weight initialization on recurrent and transformer-based models in financial asset price prediction[J]. Eastern-European Journal of Enterprise Technologies, 2025, 4(4 (136)): 19-31.

[6] ZHANG Yu. Research on Price Prediction of Financial Assets in China Based on Machine Learning[D]. Shanxi University of Finance and Economics, 2025.

[7] JIN Ye. Research on Temporal Agglomerative Clustering Method for Securities Entities[D]. Harbin Institute of Technology, 2024. DOI: 10.27061/d.cnki.ghgdu.2024.000880.

[8] ZHAI Mingrui. Research on Cross-period Spread Prediction and Arbitrage Strategy of Treasury Bond Futures[D]. Donghua University, 2025.

[9] LI Haodi. Application of ARIMA-Transformer-GNN Hybrid Model in CSI 300 Stock Index Futures Prediction[D]. Shandong University, 2025.

[10] Papavassiliou G V. Cross-asset contagion in times of stress[J]. Journal of Economics and Business, 2014, 76: 133-139.

[11] Hou M. Research on the Construction of Financial Market Sentiment Index and Its Predictive Power for Asset Prices[J]. Open Journal of Business and Management, 2025, 13(01): 514-524.

[12] Enguo G. The Inherent Law of the Unpredictability of Financial Asset Price Fluctuations: Multistability and Chaos[J]. Journal of Systems Science and Complexity, 2024, 37(2): 776-804.

[13] Shen F, Kuang J, Hu Y, et al. An enhanced risk-aware multi-task learning framework with dual-source sentiment and multi-scale decomposition for robust stock ranking forecasting[J]. Expert Systems With Applications, 2026, 323: 132462-132462.

[14] Yang R, Mao Y, Yan H, et al. AFMD: attention fusion-based multiscale decomposition network[J]. The Journal of Supercomputing, 2025, 81(9): 1074-1074.

[15] CHEN Shiting. Research on Stock Prediction and Dynamic Portfolio Based on Multi-scale Decomposition[D]. Southwestern University of Finance and Economics, 2025.

[16] Wang J, Xiao L, Hu J, et al. Forecasting LNG prices using a multi-scale decomposition learning model[J]. International Review of Economics and Finance, 2026, 108: 105258-105258.

[17] Xu X, Liu Y, Ou G, et al. Hybrid forecasting of carbon emission price in China based on multimodal data feature fusion and multiscale decomposition strategy[J]. Sustainable Futures, 2026, 11: 101847-101847.

[18] LI Haodi. Application of ARIMA-Transformer-GNN Hybrid Model in CSI 300 Stock Index Futures Prediction[D]. Shandong University, 2025.

[19] Wang J, Liu J. Two-Stage Deep Ensemble Paradigm Based on Optimal Multi-scale Decomposition and Multi-factor Analysis for Stock Price Prediction[J]. Cognitive Computation, 2024, 16(1): 243-269.

[20] BI Junyu. Research on Intelligent Stock Selection Algorithm Based on Multi-factor[D]. East China Normal University, 2024.