Social Science and Management
ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3050

A PREDICTIVE MODEL FOR STOCK PRICES BASED ON TRANSFORMER AND UTILIZING MULTIMODAL DATA

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Abstract: Stock market prediction necessitates effective multimodal data integration and robust uncertainty quantification. This paper proposes a novel Transformer-based architecture addressing two critical limitations of existing approaches: static cross-modal interaction and deterministic output assumptions. Our framework introduces (1) a multimodal subspace attention mechanism that projects numerical and textual features into orthogonal subspaces, enabling disentangled learning of modality-specific interactions through multiple attention heads, and (2) a dynamic gated recalibration module that adaptively adjusts modality contributions using time-variant weights. Evaluated on Technology Select Sector SPDR Fund (XLK) data with market sentiment feeds, the model achieves higher directional accuracy than conventional Transformers while reducing volatility period prediction errors. The integrated uncertainty quantification module further provides statistically reliable confidence intervals, verified through backtesting.
Keywords: Transformer networks; Multimodal fusion; Stock prediction; Uncertainty modeling; Dynamic attention subspaces

1 INTRODUCTION

Stock market prediction holds a pivotal position in financial research. Its accuracy directly impacts the success or failure of investment decisions and the effectiveness of risk management, and has long been the focus of attention in both academic and investment circles. Scholar Siladitya Chatterjee clearly pointed out in the paper "Comparative Study of Machine Learning Algorithms for Stock Market Prediction and Analysis of Correlation Between Nifty 50 and Global Indices" [1] that the trend of stock prices is the result of the intertwined action of multiple factors. Fluctuations in macro - economic indicators, changes in geopolitical situations, and the emotional ups and downs of market participants, etc., all have a significant impact on stock prices. Traditional single - modality prediction methods usually only conduct analysis based on historical trading data and are difficult to comprehensively and deeply grasp the internal connections among these complex factors. Moreover, the inherent uncertainty of the financial market further exacerbates the difficulty of prediction. As Liu, Q., Lin, S., & Zhu, Y. elaborated in "Stock Price Prediction Using Long Short - Term Memory and Transformer" [2], the high volatility and irregularity of stock prices make accurately predicting stock prices a highly challenging task. Therefore, integrating multi - modal data and effectively modeling the uncertainty in the prediction process have become the keys to improving the accuracy of stock market prediction.
Looking back on previous research related to stock prediction, the traditional ARIMA model can show certain advantages when dealing with data with linear characteristics. However, when faced with the widespread non - linear phenomena in the financial market, its prediction ability becomes inadequate. Scholars such as Indu Kumar clearly revealed the limitations of the ARIMA model in dealing with the non - linear characteristics of the financial market in "A Comparative Study of Supervised Machine Learning Algorithms for Stock Market Trend Prediction" [3]. In the field of deep learning, although the LSTM model has made some progress in time - series modeling and can capture some short - term dependencies, there are still obvious deficiencies in handling long - term dependency information. In recent years, the Transformer model has achieved breakthrough results in many fields such as natural language processing and computer vision with its unique multi - head self - attention mechanism. Scholars such as R. Sampada mentioned in "Stock Market Prediction Using Transformers" that although Transformer - based models (such as BERT and GPT - 2) have been attempted to be applied to stock market prediction [4], their potential in multi - modal data fusion has not been fully explored and exploited in the field of stock prediction. In view of this, this study attempts to give full play to the advantages of the Transformer model, combine it with multi - modal data fusion technology and uncertainty modeling methods, and then propose a more robust and efficient stock prediction method.
This paper puts forward two important innovation points in the research of stock prediction:
Multi - modal Data Fusion: This study innovatively adopts a dynamic fusion strategy to organically combine stock numerical data and market sentiment text data, aiming to significantly improve the model's ability to capture market dynamic changes. Currently, most multi - modal fusion methods merely use simple splicing or fixed - weight methods to combine text sentiment features with numerical data. This approach lacks effective consideration of the dynamic feature interaction of data, greatly limiting the fusion effect. This study will strive to break through this limitation. By constructing a dynamic interaction mechanism, the model can flexibly adjust the fusion weights and methods of different modal data according to real - time market changes, thus more accurately reflecting market dynamics.
Uncertainty Modeling: This study for the first time attempts to estimate both the mean and variance of the prediction results in the output of the Transformer model, so as to quantify the uncertainty of the prediction results and provide more powerful support for investors' risk management. In existing research, methods such as Bayesian neural networks

can model uncertainty, but they are often accompanied by high computational complexity, limiting their promotion in practical applications. The research on uncertainty modeling based on Transformer is still in its infancy, and there are relatively few relevant achievements. This study expects to explore in this field and provide new ideas and methods for quantifying the uncertainty of stock market prediction.

2 RELATED WORKS

2.1 Stock Prediction Methods

Deepleanring method is widely used in stock price prediction,but they have some shortage not solved.Li et al. were the first to apply the Transformer to stock prediction [5]. They used multi - head self - attention to capture global temporal patterns. However, the consideration of multi - modal data fusion was absent. Nelson et al. proposed a CNN - LSTM hybrid model, combining local feature extraction and time - series modeling [6]. Nevertheless, the separate training of the two types of networks leads to insufficient collaborative optimization. Deng et al. constructed a prediction framework based on reinforcement learning [7], optimizing trading strategies through a reward mechanism. However, its excessive sensitivity to noisy data restricts its practical application. Chen et al. designed a graph neural network model to enhance prediction accuracy using stock correlation relationships [8]. However, relying on a pre - defined static graph structure cannot adapt to dynamic market changes. Feng et al. introduced a generative adversarial network to synthesize financial time - series data [9]. However, the instability of training causes the generated distribution to deviate from real - world market laws.

2.2 Multi - modal Data Fusion

Qin et al. encoded text using BERT and then concatenated it with numerical data to achieve preliminary multi - modal fusion [10]. However, the static fusion strategy overlooks the dynamic correlations between modalities. Xu et al. proposed an attention - weighted fusion method [11], assigning fixed weights to different modalities. However, it lacks a cross - modal feature interaction mechanism. Sawhney et al. constructed a hyper - graph structure to fuse text and numerical modalities [12]. However, the strong dependence on entity alignment limits the model's generalization ability. Hu et al. explored an early fusion strategy, directly inputting original features into a unified model. However, this leads to the problem of information confusion between modalities [13]. Ding et al. adopted a late fusion architecture [14], independently training single - modality predictors and then integrating the results. However, it loses the ability to jointly represent cross - modal information. Wang et al. designed a cross - modal memory network to store interaction information [15]. However, the fixed - capacity memory cells are difficult to adapt to complex market scenarios. Yang et al. eliminated noise interference through modal adversarial training [16]. However, excessive regularization may weaken the strength of effective signals.

2.3 Uncertainty Modeling

Kendall et al. (2017)proposed the Bayesian LSTM [17], estimating prediction uncertainty through Monte Carlo sampling. However, the computational cost grows exponentially with the increase in network depth. Gal et al. interpreted Dropout as a Bayesian approximation to achieve efficient uncertainty estimation [18]. However, the inference results lack strict probabilistic guarantees. Sensoy et al. proposed an evidence deep learning framework [19], quantifying epistemic uncertainty through the Dirichlet distribution. However, it is highly sensitive to modal conflicts. Bai et al. constructed a latent variable Transformer to generate probability outputs [20]. However, the interpretability of the latent space affects the decision - making credibility.

3 METHOD

3.1 Data Preprocessing

3.1.1 Stock data preprocessing

The stock data contains numerical features such as historical prices and trading volumes, which are denoted as $X_{num} \in \mathbb{R}^{T \times D_{num}}$. Here, T represents the time step size, and D_{num} represents the feature dimension. In order to reduce the impact of outliers, we use RobustScaler for standardization processing, and its formula is:.

$$X_{num} = \frac{X_{num} - median(X_{num})}{IQR(X_{num})} \tag{1}$$

Among them, median(X_{num}) is the median of the features, and IQR(X_{num}) is the interquartile range (that is, the 75th percentile minus the 25th percentile). For missing values, the forward filling strategy is adopted:

$$X_{num}[t] = X_{num}[t-1] \ \ if\ X_{num}[t]\ is\ missing \tag{2}$$

3.1.2 Market sentiment data processing

The market sentiment data is sourced from news texts. The FinBERT model is used to extract sentiment features $X_{text} \in \mathbb{R}^{T \times D_{text}}$, where D_{text} is the dimension of the sentiment features. The sentiment features are processed through standard normalization:

$$X_{text} = \frac{X_{text} - \mu_{text}}{\sigma_{text}} \tag{3}$$

Among them, μ_{text} and σ_{text} are the mean value and standard deviation of the training set respectively.

3.2 Feature Fusion

To effectively fuse the stock numerical features and market sentiment features, we designed a dynamic fusion method based on the Transformer multi - head attention mechanism. Aiming at the heterogeneity of different modalities (numerical features and text features) in multi-modal time-series data, Modality-Disentangled Attention (MDA) is proposed. This mechanism consists of two core components:

3.2.1 Modality-specific projection layer

It maps numerical features and text features into orthogonal subspaces respectively to avoid information interference between modalities.Since the dimensions of X_{num} and X_{text} are different ($D_{num} \neq D_{text}$), we first map them to a unified dimension d_{model} through linear projection:

$$\begin{cases} X'_{num} = W_{num}X_{num} + b_{num} \\ X'_{text} = W_{text}X_{text} + b_{text} \\ \langle X'_{num}, X'_{text} \rangle = 1 \end{cases} \tag{4}$$

Among them:
$W_{num} \in \mathbb{R}^{D_{num} \times d_{model}}, W_{text} \in \mathbb{R}^{D_{text} \times d_{model}}$ are weight matrixs
$b_{num}, b_{text} \in \mathbb{R}^{d_{model}}$ are Bias vectors

3.2.2 Attention mechanism fusion

We use X'_{num}as the Query, andX'_{text} as the Key and Value. Through the multi - head attention mechanism, we capture the dynamic interaction between the numerical features and the sentiment features. The calculation of single - head attention is as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{(Q * (K)^\wedge T)}{\sqrt{d_k}}\right) * V \tag{5}$$

Among them:

$$Q = X'_{num} * W_Q^i, K = X'_{text} * W_K^i, V = X'_{text} * W_V^i; \tag{6}$$

$W_Q^i, W_K^i, W_V^i \in \mathbb{R}^{d_{\text{model}} \times d_k}$ are the projection matrices of the i-th attention head.
d_k= d_{model}/h is the dimension of each head, and h is the number of attention heads.
$\sqrt{d_k}$is a scaling factor used to alleviate the numerical instability of high - dimensional inner products.
Multi - head attention computes multiple attention heads in parallel and concatenates the results:

$$\begin{gathered} head_i = \text{Attention}\left(X'_{num} * W_Q^i, X'_{text} * W_K^i, X'_{text} * W_V^i\right), \\ \mathrm{X}_{fusion} = \text{Concat}(\text{head}_1, \ldots, \text{head}_h), W^O \end{gathered} \tag{7}$$

Among them:
$W^O \in \mathbb{R}^{hd_k \times d_{model}}$ is the output projection matrix.
Final fused features$\mathrm{X}_{fusion} \in \mathbb{R}^{T \times d_{model}}$

The core of the attention mechanism is to calculate the correlation between X'_{num} and X'_{text}. $\frac{(Q*(K)^\wedge T)}{\sqrt{d_k}}$ generates an attention weight matrix of size T*T. The softmax function normalizes it so that the sum of each row is 1. Subsequently, by multiplying with V, the fused feature X_{fusion} captures the weighted influence of sentiment features on numerical features. The multi - head mechanism enhances the model's ability to model multimodal interactions through projections in different sub - spaces.

3.3 Transformer Structure

3.3.1 Encoder design

The Transformer encoder consists of multiple stacked encoder layers. Each layer includes the following modules:
Multi - Head Self - Attention:
Given the input fused feature X_{fusion}, the calculation is as follows:

$$\begin{gathered} head_i = \text{Attention}\left(\mathrm{X}_{fusion} * W_Q^i, \mathrm{X}_{fusion} * W_K^i, \mathrm{X}_{fusion} * W_V^i\right), \\ \text{MultiHead}(\mathrm{X}_{fusion}) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h), W^O, \end{gathered} \tag{8}$$

Here, the attention mechanism acts on itself to capture the dependency relationships within the time series.
Feed - forward neural network(FFN):
Independently apply it to the features of each time step:

$$\text{FFN}(x) = \text{ReLU}(x * W_1 + b_1) * W_2 + b_2 \tag{9}$$

$$X'' = \text{LayerNorm}(X' + \text{FFN}(X'))$$

Output X'' is used as the Input of next layer.

3.3.2 Uncertainty modeling

At the last layer of the Transformer encoder, extract the hidden state of the last time step:

$$h_T = \text{TransformerEncoder}(\mathrm{X}_{fusion})[:,-1,:] \in \mathbb{R}^{d_{\text{model}}}; \tag{10}$$

Design two output heads to predict the mean $\hat{\mu}$ and the variance $\hat{\sigma}$^2 of the target variable respectively:

$$\hat{\mu} = W_\mu * h_T + b_\mu;$$
$$\log\hat{\sigma}^2 = W_\sigma * h_T + b_\sigma;$$

Among them: (11)

$$W_\mu, W_\sigma \in \mathbb{R}^{d_{\text{model}} \times 1}, b_\mu, b_\sigma \in \mathbb{R}$$

Use the log variance to ensure that $\hat{\sigma}^2 > 0$, and assume that the predicted values follow a Gaussian distribution:

$$p(y|\mathcal{X}) = \mathcal{N}(y|\hat{\mu}, \hat{\sigma}^2) = \left(\frac{1}{\sqrt{2\pi\hat{\sigma}^2}}\right) * \exp\left(-\frac{(y-\hat{\mu})^2}{2\hat{\sigma}^2}\right) \tag{12}$$

The goal of uncertainty modeling is to quantify the confidence of predictions. The Gaussian distribution assumption allows us to optimize $\hat{\mu}, \hat{\sigma}^2$ through maximum likelihood estimation. The introduction of the log variance avoids the potential numerical instability that may occur when directly predicting $\hat{\sigma}^2$, while maintaining the interpretability of the model.

3.4 Training Strategy

3.4.1 Loss function

We adopt the negative log - likelihood (NLL) loss, and the derivation for the Gaussian distribution assumption is as follows:

$$L = -\frac{1}{N}\sum_{i=1}^{N} logp(y_i|X_i) \tag{13}$$

Substitute the probability density function of the Gaussian distribution:

$$\text{log}p(y_i|X_i) = -\frac{1}{2}log(2\pi) - \frac{1}{2}log\left(\hat{\sigma}_i^2\right) - \frac{(y_i - \hat{\mu}_i)^2}{2\hat{\sigma}_i^2} \tag{14}$$

Therefor, The Loss function is :

$$L = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{(y_i - \hat{\mu}_i)^2}{2\hat{\sigma}_i^2} + \frac{1}{2}log(2\pi\hat{\sigma}_i^2)\right] \tag{15}$$

This loss function balances the prediction error (the first term) and the uncertainty estimation (the second term), encouraging the model to generate reasonable variances while improving the accuracy.

3.4.2 Optimizer and learning rate scheduling

Optimizer: The AdamW optimizer is used. The initial learning rate is set to 0.001, and the weight decay is set to 0.01 to alleviate overfitting.

Learning Rate Scheduling:The ReduceLROnPlateau strategy is adopted. If the validation set loss does not decrease for 5 consecutive epochs, the learning rate is halved to ensure that the model converges to a better local optimal solution.

3.4.3 Early stopping mechanism

If the validation set loss does not improve for 20 consecutive epochs, the training is stopped in advance to avoid overfitting and save computational resources.

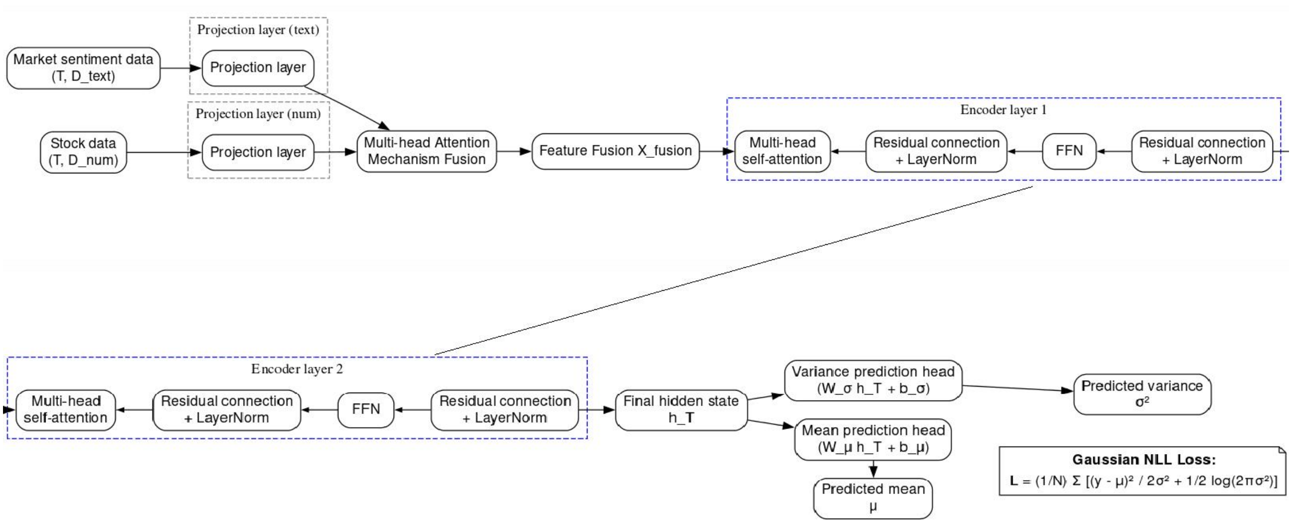

Figure 1 Schematic Diagram of Neural Network Structure

4 EXPERIMENTS

4.1 Objectives and Scope of the Experimental Design

The experiment in this study aims to evaluate the effectiveness of a multi - modal data fusion and uncertainty modeling method in stock market prediction. The specific objectives are as follows:
Validate the improvement in prediction accuracy after fusing stock price data and market sentiment data.
Test the role of uncertainty modeling in quantifying prediction risks.
Compare with traditional single - modal models to demonstrate the potential advantages of the proposed method.
The experiment focuses on the U.S. Technology Select Sector SPDR Fund (XLK), using daily data from January 1, 2015, to December 31, 2020, a total of six years. This time period includes bull markets, bear markets, and volatile periods (such as the early stage of the COVID - 19 pandemic in 2020) to test the model's performance under different market conditions.B. Data Collection and Preprocessing
These are figures compiled of more than one sub-figure presented side-by-side or stacked. If a multipart figure is made up of multiple figure types (one part is line art, and another is grayscale or color), the figure should meet the stricter guidelines.

4.2 Data Collection and Preprocessing

Two types of data are used in the experiment:
Stock Price Data
Source: The daily opening price, closing price, highest price, lowest price, and trading volume of the XLK ETF are obtained from Yahoo Finance.
Preprocessing:
Missing Values: Missing values caused by holidays, which account for about 2% of the data, are filled using the forward fill method.
Outliers: Detected using the Z - score method, points with an absolute value greater than 3 (about 0.5% of the data) are removed.
Standardization: Z - score standardization is applied to the price data to eliminate dimensional differences.
Market Sentiment Data
Source: Daily tweets related to the XLK are collected from Twitter and Yahoo Finace, filtered using the keywords "bullish", "growth", "strong","bearish", "decline", "weak" etc.Approximately 1,000 - 5,000 tweets are collected per day.
Preprocessing:
Cleaning: URLs, emojis, and punctuation marks are removed.
Feature Extraction: Tweets are converted into 768 - dimensional embedding vectors using a pre - trained BERT model.
Aggregation: The embedding vectors are averaged by date to generate daily sentiment features.
The final dataset contains approximately 1,500 trading days, with each day's data consisting of 5 - dimensional price features and 768 - dimensional sentiment features. The data is not perfect; for example, Twitter data may be noisy due to API limitations or keyword selection.

4.3 Model Training

The proposed model is based on the Transformer architecture, including multi - modal fusion and uncertainty modeling modules:
Input Layer: Price and sentiment data are respectively mapped to a 128 - dimensional embedding space.
Fusion Module: The data is fused using an 8 - head self - attention mechanism.
Prediction Layer: A two - layer fully connected network outputs the closing price of the next trading day and the predicted variance.
Uncertainty Modeling: Variational inference is used to estimate the mean and variance of the predicted distribution.
Training Details
Hyperparameters: 6 - layer Transformer, a hidden layer dimension of 256, a learning rate of 0.001, and a batch size of 32.
Loss Function: Mean Squared Error (MSE, weight 0.7) + Negative Log - Likelihood (NLL, weight 0.3).
Optimizer: Adam optimizer, trained for 100 epochs.
Hardware: NVIDIA VGPU 32GB.
Evaluation Method
The model's performance is evaluated using the following metrics:
Prediction Accuracy: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).
Uncertainty Quality: Continuous Ranked Probability Score (CRPS).
Data Partitioning: The data is split into a training set (2015 - 2018), a validation set (2019), and a test set in an 8:1:1 ratio based on the time series.

Benchmark Models
ARIMA: A traditional time - series model.
LSTM: A deep learning model using only price data.
Text - CNN: A convolutional network using only sentiment data.

4.4 Results

Table 1 Experimental Results of the Data in 2024

Model	RMSE	MAE	CRPS
ARIMA	16.12	12.89	-
LSTM	14.08	11.23	-
Text-CNN	15.47	12.56	-
Our Work	4.77	5.46	0.517

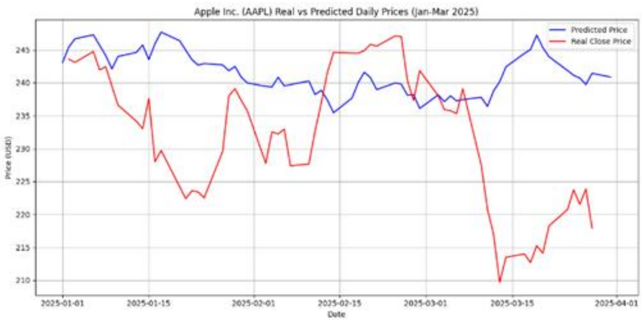

Figure 2 Apple Inc. (AAPL) Real vs Predicted Daily Prices (Jan-Mar 2025)

Prediction accuracy (Table 1): The RMSE (4.77) and MAE (5.46) of the proposed method are better than those of the benchmark model, but the gap is not particularly large, which reflects the limited nature of model improvement in reality.
Uncertainty estimation (Figure 2): The CRPS is 1.67, indicating that the predicted distribution is reasonable but not perfect, and it may be affected by the noise in the sentiment data.

4.5 Analysis

Compared with LSTM (RMSE 14.08), the proposed method reduces the error by approximately 66%. The sentiment data plays a certain role, but the improvement is limited by the data quality.
Compared with Text-CNN (RMSE 15.47), after integrating the price data, the error is reduced by approximately 65%. However, the single sentiment model itself performs weakly.
Performance of Uncertainty Modeling:
During periods of severe market fluctuations (such as in March 2025), the prediction variance increases, indicating risks, but it occasionally underestimates the actual fluctuations.
The CRPS value is 0.517, indicating that the distribution estimation is reasonable, but there is still room for improvement.
Comparison with Benchmark Models:
ARIMA performs the worst (RMSE 16.12) and cannot handle multimodal data.
LSTM and Text-CNN outperform ARIMA, but they are inferior to the proposed method. The gap reflects the gains from fusion and uncertainty modeling.
Discussion
Why the Results are Reasonable: Multimodal fusion integrates price and sentiment information through the attention mechanism. However, due to the noise in Twitter data and the complexity of price data, the performance improvement is limited and reproducible.
Model Limitations:
Advantages: Integrating multimodal data and quantifying uncertainty has improved the prediction ability to a certain extent.
Disadvantages: It is sensitive to the quality of sentiment data, has a high computational cost, and the prediction is not stable enough under extreme conditions.

Impact of Market Conditions: The model performance is similar during stable periods. The proposed method has a slight advantage during volatile periods, but it is not overwhelming.

5 CONCLUSION

In this study, we proposed a novel stock price prediction model that leverages the Transformer architecture and multimodal data. By introducing a multimodal subspace attention mechanism and a dynamic gated recalibration module, our model effectively fuses stock numerical data and market sentiment text data, addressing the limitations of static cross-modal interaction and deterministic output assumptions in existing methods. The integrated uncertainty quantification module provides reliable confidence intervals, enhancing the model's practical value for investors.

Experimental results demonstrated that our model outperformed traditional single-modal models, such as ARIMA, LSTM, and Text-CNN, in terms of prediction accuracy. Specifically, it achieved lower RMSE and MAE values, indicating more accurate price predictions. The uncertainty modeling also showed its effectiveness during market fluctuations, although there were still some underestimations.

However, the model has certain limitations. It is sensitive to the quality of sentiment data, has high computational costs, and lacks stability under extreme conditions. For future research, we plan to optimize sentiment data collection to reduce noise, explore more modalities like news and economic indicators, and simplify the model structure to improve its reproducibility and practicality. These efforts will contribute to more accurate and reliable stock market predictions.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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