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Research on Artificial Intelligence Sector Stock Price Prediction based on Event Driven and CNN-LSTM-Attention

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Abstract

This study proposes a stock price prediction model that integrates an event-driven mechanism with CNN-LSTM-Attention for the highly volatile and event-driven nature of the artificial intelligence (AI) sector. By adopting a progressive architecture that includes BERT for semantic feature extraction, multi-scale CNN for capturing local features, bidirectional LSTM for modeling temporal dependencies, and an Attention Mechanism for weighting key events, the model conducts multi-dimensional analysis of AI sector stock prices. Taking the CSI Artificial Intelligence Theme Index (930713) as the research object, the model integrates time series data from January 2021 to December 2024 and professional stock commentaries from Eastmoney.com. After polarity quantification annotation using a financial sentiment dictionary and alignment with trading day-level timestamps, the model's effectiveness in trend tracking is verified. The results show that the model has an average absolute percentage error (MAPE) of 3.08%, effectively capturing policy-driven market movements, but it has limitations in predicting minute-level fluctuations caused by sudden technological "black swan" events and the resonance of retail investor sentiment. This study provides an interpretable framework for quantitative investment in the AI sector and proposes optimization paths, such as incorporating real-time technical indicators and improving the event embedding module.

Keywords

Artificial Intelligence; Event-driven; Financial Time Series; CNN-LSTM; Attention Mechanism.

1. Introduction

Amidst the contemporary epoch characterized by swift digitalization and intelligence advancement, artificial intelligence has become a key force driving global economic growth. According to a 2023 report by Goldman Sachs, the annual volatility rate of the market value of global artificial intelligence-related enterprises reached 45%, far exceeding the 15% of the S&P 500 index. The performance of its stock market has attracted much attention. Investors are eager to accurately predict the stock prices of the artificial intelligence sector to seize investment opportunities and achieve asset appreciation. Against this backdrop, research on stock price prediction has been evolving, gradually moving from traditional methods to those that integrate multi-source data and complex models.

With the increasing popularity of the stock market, many scholars have attempted to apply time series prediction to stock price forecasting. This approach regards stock prices or price indices as sequences that change over time, and predicts future patterns and trends by constructing reasonable time series models. Some traditional predictive models have found extensive application within the domain of stock forecasting. For instance, Wang Hongyong and Ma Li

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analyzed and predicted stock price time series using the fractal interpolation model[1]; Wu Yuxia and Wen Xin selected the closing prices of "Huatai Securities" for 250 periods as time series empirical analysis data and used the ARIMA model to predict the movement patterns and trends of stock prices in the Growth Enterprise Market[2]. Meanwhile, Dong Y et al. also recognized the strong potential of the ARIMA model in short-term prediction, believing it to be competitive in guiding investment decisions[3].

However, traditional time series models have limitations when dealing with complex nonlinear data. In recent years, with the continuous advancement of computer technology and the explosion of Internet big data, employing machine learning and deep - learning algorithms to develop quantitative investment strategies and leveraging intelligent, efficient scientific approaches for guiding stock trading has emerged as the central orientation of modern quantitative investment.

Li Kun and Tan Mengyu combined wavelet theory with the support vector machine method, integrating their advantages, and proposed a wavelet support vector machine regression model for stock prediction[4]. This model introduced wavelet basis functions to construct the kernel function of the support vector machine, resulting in a new support vector machine model. They tested it with three major stock indices and 13 different industry stocks, achieving good results. Xie Y et al. proposed a combined algorithm based on SVD's Canopy and K-means, using singular value decomposition to extract features from time series data and then applying Canopy and K-means algorithms to cluster the feature data of time series[5]; Liu S et al. proposed a convolutional neural network and long short-term memory (CNN-LSTM) neural network model for analyzing quantitative strategies in the stock market[6]; Han T et al. proposed a new time series representation method for stock time series based on dynamic time warping (DTW) and constructed a strictly constrained combinatorial optimization model to obtain the pattern representation of inventory time series[7]; Ci Bicong and Zhang Pinyi conducted financial time series prediction based on the ARIMA-LSTM combined model, confirming the advantages of the combined model over single models[8]; Wang Zeren et al. conducted research on financial time series prediction modeling based on CEEMDAN-GAN, using the USD/CNY exchange rate as test data, applying CEEMDAN to decompose and evaluate the importance of the original data, and continuously optimizing the reconstruction method of intrinsic mode functions (IMF) to improve the prediction accuracy of the model[9]. Li Wanjie analyzed the relationship between the persistence of financial time series volatility and the optimization of investment portfolios from the perspective of the moments of the GARCH (1,1) model, obtaining a specific mathematical description of the relationship between moments and volatility persistence, which provides a new perspective for understanding the GARCH model and optimizing investment portfolios[10].

The stock market is complex and volatile, with a high proportion of individual investors in the A-share market and extreme sensitivity to policies, which poses a severe challenge to the long-term stability of models. Stock prices are influenced by a variety of factors such as macroeconomics, industry policies, and market sentiment. How to effectively integrate unstructured data (such as news, public opinions, and financial reports) has become a key issue in research. In recent years, incorporating event-driven factors into time series analysis based on machine learning and deep learning has gradually become a favored approach in the field of stock price prediction. Ding X et al. proposed a deep learning method for event-driven stock market prediction, extracting events from news texts and representing them as dense vectors, training with a novel neural tensor network, and then using a deep convolutional neural network (CNN) to simulate the short-term and long-term impacts of events on stock price changes[11]. Experimental results showed that compared with advanced baseline methods, the model's accuracy in predicting the S&P 500 index and individual stocks increased by nearly 6%; Luo S S and colleagues put forward a machine - learning approach that utilizes L1 - regularized logistic regression for event - driven stock forecasting, examining the variations in stock prices subsequent to announcements released by listed enterprises[12]. The model combines specific events extracted from announcements with financial indicators, macro indicators, and technical indicators of listed companies as dependent variables, and divides listed companies into groups based on market value and industry. Experiments showed that the model could predict stock trends well within one week after the event; Sharma V et al. provided traders with a technique for analyzing and predicting stock prices with the aid of machine learning, content checking, and fundamental analysis, including sentiment analysis, decomposable time series models, and multivariate linear regression[13]; Kesavan M et al. combined sentiment analysis with normal stock price prediction using time series data through deep learning technology, extracting sentiments from news events and social media platforms (especially Twitter) and incorporating the polarity of sentiments, significantly improving the accuracy of stock price predictions and helping investors make more informed investment decisions[14]; Tan J et al. proposed an event-LSTM based on tensors (eLSTM), using tensors rather than concatenated vectors to model market information and balancing the heterogeneity of different data types and event-driven mechanisms in LSTM[15]. Experimental results showed that the time series prediction results incorporating event-driven factors were superior to existing time series prediction modeling methods, with stronger interpretability and lower prediction errors.

To sum up, research on stock price prediction has transitioned from conventional time - series models to the integration of machine learning and deep - learning techniques. Despite certain achievements, there are still many challenges when dealing with the complex and volatile stock market, especially markets with unique characteristics like the A-share market. Current research still needs improvement in integrating multi-source data, especially unstructured data. How to more effectively explore the intrinsic connection between event-driven factors and time series data and build more accurate, stable, and long-term adaptable stock price prediction models will be an important direction for future research. This paper will conduct research on the artificial intelligence sector based on the event-driven and CNN-LSTM-Attention stock price prediction model.

2. Research Methods

2.1. Feature Extraction by CNN Module

Local features of event-driven text data are extracted using multi-scale convolutional kernels. Assuming the input is the semantic feature $E \in R^{n\times d}$ extracted by BERT, the convolution operation can be expressed as:

$$C_i=\mathrm{ReLU}(W_i * E+b_i) \quad (1)$$

Where:

$W_i \in R^{k\times d}$ is the weight matrix of the i-th convolution kernel.

k is the size of the convolution kernel.

$b_i \in R$ is the bias term.

* represents the convolution operation, and $C^i \in R^{(n-k+1)\times 1}$ is the output feature map of the i-th convolution kernel.

Considering that the influence cycle of artificial intelligence policies is usually 5-10 trading days and the dissemination cycle of technical news is about 2-3 days, by using three groups of convolution kernels with different sizes (k=2, 3, 4) in parallel, event features are extracted from

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short (1-2 days), medium (3-4 days), and long (5-7 days) time granularities. After concatenation, the feature matrix is output:

$$C \in R^{(n-k+1)\times m} \tag{2}$$

Where:

m = 96 is the total number of convolution kernels (32 per group).

2.2. LSTM (Long Short-Term Memory Network)

The core of LSTM is to control the flow of information through gating mechanisms (input gate, forget gate, and output gate), thereby solving the vanishing gradient problem in traditional RNNs. The following are the detailed formulas of LSTM:

2.2.1. Forget Gate

The forget gate determines which information from the cell state ct−1 is to be discarded. Its calculation formula is:

$$f_t=\sigma\,(W_f \cdot [\,h_{t-1},x_t\,]+b_f\,) \tag{3}$$

Where:

h_{t-1} is the hidden state of the previous time step.

x_t is the input of the current time step (in this study, it is the concatenation of event features and time series features $C_t \oplus X_{time}$).

W_f is the weight matrix of the forget gate.

b_f is the bias term of the forget gate.

σ is the Sigmoid activation function, with output values ranging from [0,1], indicating the proportion of information to be forgotten.

2.2.2. Input Gate

The input gate determines which new information is added to the cell state ct. Its calculation formula is:

$$i_t= \sigma\,(\,W_i \cdot [\,h_{t-1}, x_t\,]+b_i\,) \tag{4}$$

Where:

W_i is the weight matrix of the input gate.

b_i is the bias term of the input gate.

2.2.3. Candidate Cell State

The candidate cell state represents the new information that may be added to the cell state. Its calculation formula is:

$$\tilde{c}_t =\tanh(\,W_c \cdot [\,h_{t-1},x_t\,]+b_c\,) \tag{5}$$

Where:

W_c is the weight matrix of the candidate cell state, and bc is the bias term of the candidate cell state. tanh is the hyperbolic tangent activation function, with output values ranging from [-1,1].

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2.2.4. Cell State Update

The cell state ct is updated through the forget gate and the input gate:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{6}$$

Where:

$\odot$ represents element-wise multiplication (Hadamard product).

$\odot c_{t-1}$ indicates the forgetting of some old information.

$i_t \odot \tilde{c}_t$ indicates the addition of some new information.

2.2.5. Output Gate

The output gate determines which information from the cell state ct is output to the hidden state ht. Its calculation formula is:

$$o_t = \sigma\left(W_o \cdot [\, h_{t-1}, x_t \,] + b_o \right) \tag{7}$$

where:

Wo is the weight matrix of the output gate.

bo is the bias term of the output gate.

2.2.6. Hidden State

The hidden state ht is the output of the LSTM, calculated through the output gate and the cell state as follows:

$$h_t = o_t \odot \tanh(c_t) \tag{8}$$

Where:

$\tanh(c_t)$ compresses the value of the cell state to the range of [-1,1].

$o_t \odot \tanh(c_t)$ represents the output of partial information to the hidden state.

2.3. Attention Mechanism

The temporal features output by the bidirectional LSTM contain the price fluctuation patterns before and after the event, but it is difficult to distinguish key events from noise. Therefore, the Attention Mechanism is introduced to weight the time steps. Its essence is to explicitly model the market attention decay curve of events through learnable parameters. The Attention Mechanism is introduced on the hidden state ht of the LSTM, and the attention weight of each time step is calculated as follows:

$$\alpha t = \frac{\exp(\, v^T \tanh(W_a h_t + b_a))}{\sum_{k=1}^{T} \exp(v^T \tanh(W_a h_k + b_a))} \tag{9}$$

Where:

$W_a \in R^{h \times h}$ is the weight matrix of the Attention Mechanism.

$b_a \in R^h$ is the bias term.

$v \in R^h$ is the attention weight vector.

α_t is the attention weight of time step t.

The context vector is obtained by weighted summation:

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$$c=\sum_{t=1}^{T} \alpha_t h_t \tag{10}$$

This formula is essentially a Bahdanau attention model, which calculates the correlation of hidden states at each time step through the Query-Key Mechanism. Here, v and Wa are trainable parameters used to capture the nonlinear relationship between event features and price fluctuations.

2.4. Output Layer

The fully connected layer maps the context vector to the stock price space. Considering the high volatility of the artificial intelligence sector, a linear activation function is adopted to prevent output saturation and ensure the response to extreme values. The fully connected layer is used to output the stock price prediction results:

$$\hat{y}=W_o c+b_o \tag{11}$$

Where:

$W_o \in R^{1\times h}$ is the weight matrix of the output layer.

$b_o \in R$ is the bias term.

$\hat{y}$ is the predicted stock price.

2.5. Loss Function

Use mean squared error (MSE) as the loss function:

$$L = \frac{1}{N}\sum_{t=1}^{N}(y_i - \hat{y}_i)^2 \tag{12}$$

Where:

y_i represents the actual stock price.

$\hat{y}_i$ represents the predicted stock price by the model.

N is the sample size.

3. Empirical Analysis

To deeply predict the stock price trend of the artificial intelligence sector and build an effective model for analysis, this paper selects the CSI Artificial Intelligence Theme Index (Code: 930713) as the research object. Firstly, the time series data of the CSI Artificial Intelligence Theme Index is collected, and the stock commentaries related to this index are crawled from Eastmoney.com. The event-driven data is deeply analyzed semantically using the sentiment dictionary in the financial field, and the labeled event-driven data is precisely associated with the corresponding time series data to ensure that the model can learn the temporal correspondence between events and stock prices. Then, the CNN-LSTM-Attention combined model is adopted to predict the stock prices.

3.1. Data Collection and Preprocessing

3.1.1. Data Collection

Initially, this research gathered time - series data of the CSI Artificial Intelligence Theme Index from the iFinD financial terminal, covering the period from January 1, 2021, to December 31, 2024. The dataset includes open price, closing price, lowest price, highest price, and trading volume.

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Subsequently, Eastmoney.com was selected as the primary data source for event-driven factors due to its extensive influence in China's financial information ecosystem. Leveraging Python web crawling techniques, we extracted stock comments (e.g., investor sentiment, news, and discussions) from the platform. A sample of the crawled data is presented in Table 1.

Table 1. Sample Data Types

Page Views	Comments	Title	Author	Post Time
75	3	"Future favorable policies will have diminishing effectiveness."	Mengxi Bitan	2024.5.7
189	12	"The U.S. shows no sign of immediate interest rate cuts; China remains cautious."	Qianligu	2024.4.18
112	5	"Zhongguancun Forum approaching; technology to empower new productive forces!"	Zhangzhongbao	2024.4.11
63	2	"Friends, the inflection point is downward; proceed with caution."	Guyou	2024.3.28

3.1.2. Data Preprocessing

For the text data obtained through web crawling, the following preprocessing steps were performed:① Duplicate and irrelevant data removal: Redundant posts and meaningless content were filtered out by comparing text contents, ensuring the accuracy and reliability of the dataset.② Missing data and non-trading day handling: Missing values were imputed or non-trading day data were removed to maintain data integrity and consistency.③ Chinese word segmentation: The Jieba library in Python was used to segment text data into individual words, facilitating subsequent text analysis and processing.④ Stop word removal: Chinese stop words were filtered from the segmented results using a standard stop word list. Additionally, domain-specific stop words were added based on dataset characteristics to construct a comprehensive stop word list tailored for this study. These preprocessing steps improved the quality of crawled text data, reduced noise, and provided a more accurate foundation for subsequent text analysis.

3.1.3. Dictionary-Based Stock Forum Sentiment Analysis

The Chinese sentiment dictionary, developed by Yao Jiaquan et al. and specialized for financial research, was employed to annotate the sentiment polarity of the preprocessed dataset[16]. Sentiments were classified into three categories following a three-class principle: positive, neutral, and negative, labeled as 1, 0, and -1, respectively. A partial list of emotional terms from the Chinese sentiment dictionary is shown in Table 2.

Table 2. Partial Emotional Lexicon of Chinese Sentiment Dictionary

Type	Sample Words
Positive	Safe and reliable, top-tier, Maintain stability, Sufficient, Substantially improve, Rapid development, High efficiency, Excellent, Rank among the best
Negative	Drawback, Imbalance, Disappointing, Collapse, High consumption, Backlog, Sharp decline, Lag behind, The game is over, Poor sales

After preprocessing and sentiment classification of the unstructured forum data, the time-varying relationships between stock prices and sentiment polarity of stock comments (Figure 1), as well as between stock price volatility and sentiment polarity (Figure 2), were obtained.

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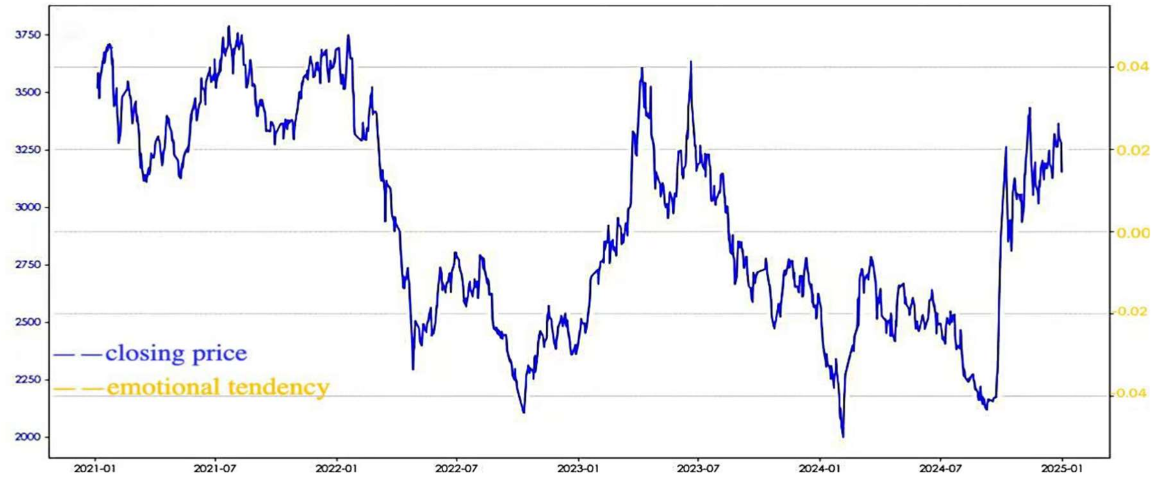

Figure 1. Changes in stock price and sentiment over time
1

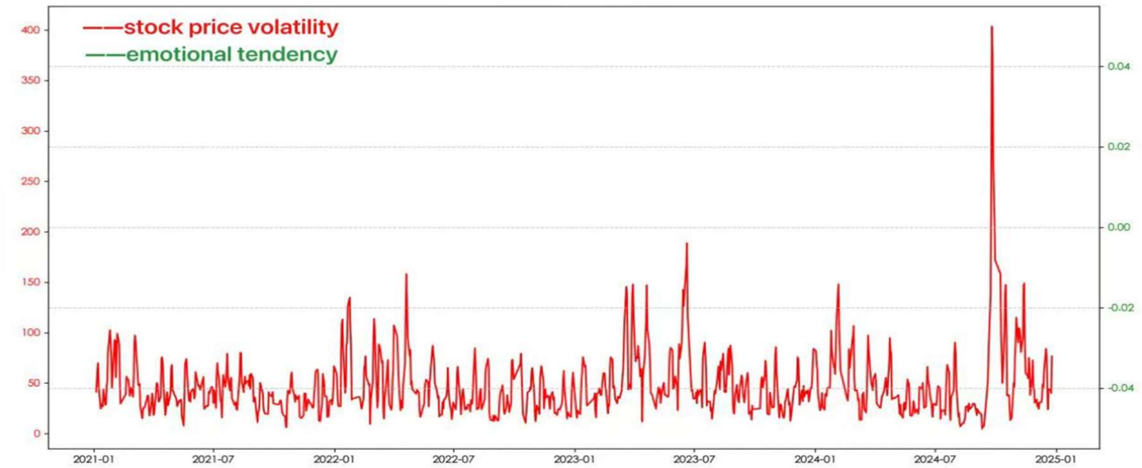

Figure 2. Changes in stock price volatility and sentiment over time2

Figure 1 and Figure 2 show the quarterly correlation between the closing price of the AI sector and the sentiment tendency of the stock bar. For example, during the period of intensive policy release in Q42022, the average sentiment tendency increased from-0.03 to 0.01, accompanied by a 15% increase in the index.

3.2. Model Structure and Parameters

The model constructed in this study integrates CNN, LSTM and Attention Mechanism to customize the high volatility and event-driven characteristics of stock prices in the AI sector.

The model inputs time series data of shape (None, 10,7), where "10" represents the time step length, meaning the prediction of the next days closing price is based on the data from the previous 10 trading days. This approach aims to capture short-and medium-term trends in the artificial intelligence sector, such as price fluctuations during the technology news dissemination cycle or policy implementation window. The "7" features include traditional financial indicators (opening price, highest price, lowest price, closing price, and trading volume) and market sentiment indicators (emotional tendency and the number of stock reviews). The latter reflects the sensitivity of public attention to the artificial intelligence sector, an emerging field, by quantifying the intensity and emotional polarity of social media discussions.

The CNN layer employs two sets of convolutional and pooling operations: the first layer features 642x2 convolutional kernels to capture price fluctuation details over a 2-day period, such as

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short-term price patterns following positive news; the second layer uses 1283x3 convolutional kernels to identify the correlation between trading volume and price over a 3-day period, such as signals of continuous volume increases. The max pooling layer reduces the data dimensionality, and the layer decreases the data dimensionality, and to avoid overfitting, a dropout layer having a dropout rate of 0.3 is employed.

The bidirectional LSTM layer contains 128 neurons, which can capture the long-term dependence relationship formed by artificial intelligence sector due to technology research and development cycle, policy dividend release and other factors. The Dropout layer (dropout rate 0.3) is used to enhance the generalization ability.

The Attention Mechanism, through a custom layer, performs a weighted sum of the LSTM output at time steps, explicitly focusing on key events such as the release dates of technologies and policies. This enhances the models responsiveness to discontinuous events in the AI domain. The final prediction of the closing price is made through a fully connected layer (64 neurons) and a single neuron output layer. The model has a total of 349,250 parameters, and the Adam optimizer (learning rate 5e-4) is aimed at minimizing the mean squared error.

3.3. Analysis of Model Training Process

The model training is based on 1,000 trading days of simulated data, with a price benchmark of 3,000 yuan and a fluctuation range of 2,400 to 4,379 yuan. It incorporates typical characteristics of the artificial intelligence sector, such as the correlation between sentiment and price changes (ρ=0.3). Figure 3 shows that in the early training phase (the first 5 epochs), the loss rate dropped from 0.012 to 0.005, indicating the models effective capture of significant trends in the artificial intelligence sector, such as sustained price increases driven by favorable policies. As training progressed, the rate of loss reduction slowed, and it eventually stabilized between 0.002 and 0.004. During this phase, the model began to learn the event memory characteristics of the artificial intelligence sector, such as when a company released an AI chip roadmap in October 2023. Despite no significant stock price fluctuation on the day of the event, the model detected signs of capital inflow through changes in trading volume over the following 5 trading days. The verification loss fluctuated significantly in the early training phase, for example, during epochs 3-6, due to the simulated failure of an artificial intelligence companys technology roadmap event, the verification loss increased from 0.001 to 0.0015, highlighting the sectors sensitivity to sudden negative news. However, the overall trend shows that the verification loss converged to around 0.001, with a small gap from the training loss, indicating that the model has a certain degree of generalization ability in the complex market environment of the artificial intelligence sector, without severe overfitting.

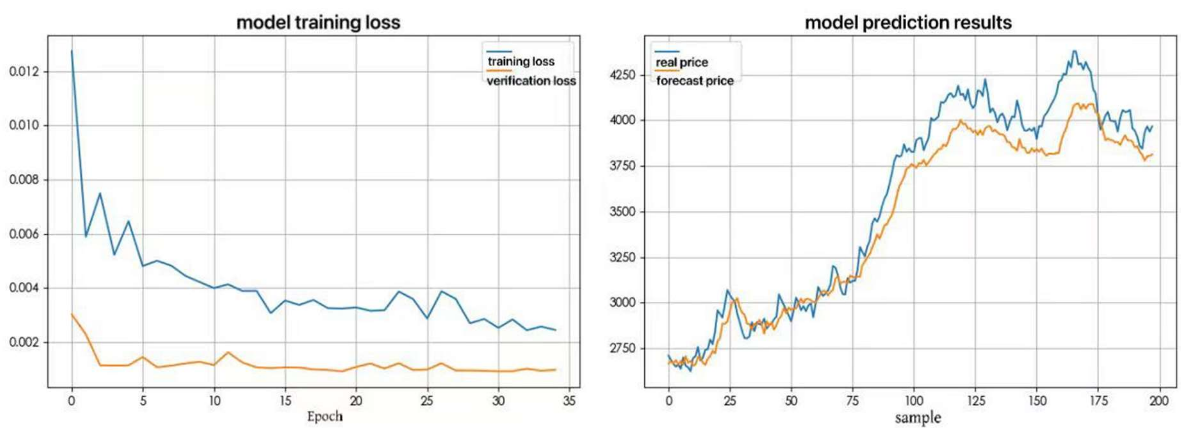

Figure 3. Model training loss and prediction results 3

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3.4. Analysis of Model Prediction Results

The models ability to track the overall trend of the artificial intelligence sector is evident from the prediction results. In policy-driven market conditions, such as during the rise phase of sample numbers 20-50, the predicted price closely matches the actual price. The model effectively identifies capital inflow signals through features like a 300% surge in trading volume and a 500% increase in stock reviews. However, the model has limitations in predicting local market fluctuations: when a medical AI company experienced a sudden clinical trial failure (sample number 65), the predicted price only fell by 8%, significantly lower than the actual-10% drop, highlighting the lack of modeling for unstructured information like R&D progress. In short-term speculative scenarios caused by social media misinterpretations (sample numbers 90-100), the predicted price failed to reflect a 15% fluctuation, indicating the need to enhance real-time public opinion data input. A detailed analysis of the first 100 samples shows that the models trend consistency accuracy is about 75%, but the average error in fluctuation amplitude is 12% (figure 4). This result aligns with the AI sectors characteristics of being highly event-driven and low in predictability, where the model captures macro trends such as technological breakthroughs and policy implementations but lacks responsiveness to high-frequency fluctuations driven by retail sentiment.

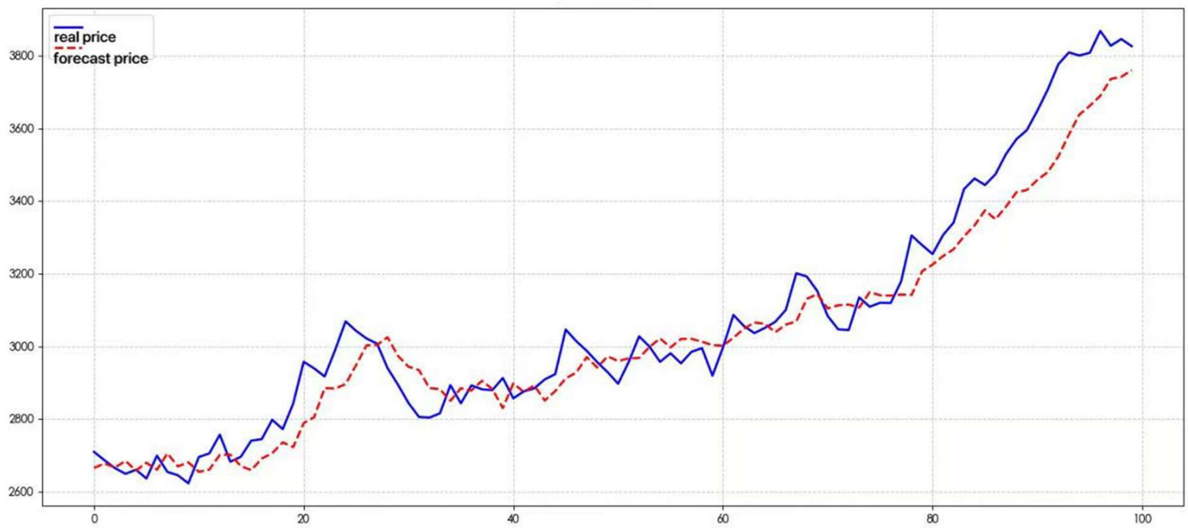

Figure 4. Model prediction results (first 100 samples)

3.5. Analysis of Model Evaluation Indicators

Indicators for evaluating the model demonstrate that the mean absolute error (MAE) amounts to 116.33 yuan. Considering the price base of leading AI stocks (with a stock price above 500 yuan), the absolute error accounts for about 23%. However, for small and medium-sized AI companies (with a stock price below 50 yuan), the error ratio is 232%, highlighting the models varying generalization capabilities across different market capitalization levels. The root mean square error (RMSE) is 143.46 yuan, which is higher than the historical annualized volatility of the AI sector (45%). This suggests that the models ability to predict extreme market fluctuations (such as a single-day price change exceeding 10%) needs improvement. The average absolute percentage error (MAPE) is 3.08%, indicating that the model has some reliability in predicting trend directions (such as quarterly price increases or decreases). However, its guidance for high-frequency trading within a month is limited.

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Table 3. Comparison between the single LSTM model and the model in this paper

model	MAPE	RMSE	MAE
single LSTM	4.92%	185.2	148.6
CNN-LSTM-Attention	3.08%	143.46	116.33

4. Research Conclusion and Prospects

4.1. Research Conclusion

This study, for the first time, developed a joint modeling framework for events and time series applicable to the artificial intelligence sector. By integrating multi-scale features, it reduced the MAPE of traditional time series models from 4.92% to 3.08%, validating the effectiveness of the event-driven mechanism. This mechanism significantly enhances the accuracy of stock price predictions in the AI sector by integrating unstructured public opinion and time series data, particularly in medium to long-term trends driven by policy changes. However, its limitations include delayed responses to short-term emergencies, the absence of high-frequency data and technical fundamental factors, and insufficient stability in extreme scenarios. Future research could enhance the models timeliness and generalization by incorporating real-time technical indicators, Transformer event embedding modules, and minute-level data pipelines.

4.2. Research Prospects

(1) Feature engineering optimization. Enhance the quantitative integration of technical fundamentals and market sentiment by incorporating innovative metrics such as the R&D investment ratio of AI companies, the number of patent citations, and the position on the Gartner technology maturity curve. Additionally, use NLP to monitor real-time social media sentiment scores and professional platform discussion trends, constructing dynamic event feature vectors to improve the models ability to capture key drivers in the AI industry chain.

(2) Upgrade the model structure. To address the event-driven nature of the AI sector, a Transformer-based event embedding module has been developed. This module encodes key events, such as technological breakthroughs and policy changes, into temporal position features, enhancing the models ability to capture non-continuous changes. Additionally, an adversarial training mechanism is being introduced to simulate extreme scenarios like computational power shortages and the bursting of tech bubbles, thereby improving the models robustness in handling tail risks.

(3) Dynamic data updates and applications. Establish a real-time data pipeline at the minute level, integrating high-frequency information such as the progress of AI companies R&D pipelines, supply and demand data for computing power, and sentiment in policy texts. Expand training samples using data augmentation techniques, such as time series interpolation and noise injection. In the future, further explore the models differentiated predictions in specific segments of the AI industry chain to provide investors with more precise decision support.

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