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Efficient Market Signal Prediction for Blockchain HFT with Temporal Convolutional Networks

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Abstract: High-frequency trading in the blockchain market has extremely high time sensitivity and complex market dynamics. Traditional time series modeling methods have problems with low computational efficiency and difficulty in capturing long-term dependencies in trading signal prediction. To address this challenge, this study proposes a trading strategy optimization method based on temporal convolutional networks (TCNs). TCN improves the modeling ability of market dynamics through causal convolution and dilated convolution mechanisms while ensuring efficient parallel computing capabilities. Experimental results show that this method is superior to traditional models in terms of prediction accuracy, cumulative yield, and risk control and significantly improves the stability of trading strategies. In addition, the contribution of TCN key components to trading strategy optimization is analyzed through ablation experiments, verifying the importance of dilated convolution and residual connections in improving the ability to predict trading signals. This study provides an efficient and accurate intelligent optimization solution for blockchain high-frequency trading and provides new ideas for the strategy design of future decentralized trading markets.

Keywords: Blockchain high-frequency trading, temporal convolutional networks, trading strategy optimization, market signal prediction, deep learning.

1. Introduction

The rise of blockchain technology has brought revolutionary changes to the financial market, especially in the field of high-frequency trading (HFT). The improvement of transaction speed and data processing capabilities enables market participants to gain market advantages in an unprecedented way. The decentralized nature of blockchain improves transaction transparency but also increases market volatility and transaction complexity [1,2]. As more and more exchanges adopt blockchain technology, the optimization of high-frequency trading strategies has become an important topic in current financial engineering and algorithmic trading research. However, the transaction data of the blockchain market has the characteristics of high dimension, nonlinearity, and non-stationarity. Traditional time series analysis methods such as autoregressive model (AR) and moving average (MA) are difficult to effectively capture market dynamics. Therefore, finding an efficient trading strategy optimization method that can adapt to the characteristics of the blockchain market has become the key to current research [3].

In recent years, deep learning has been increasingly used in financial markets, especially in the field of time series prediction. Recurrent neural networks (RNN) and long short-term memory networks (LSTM) are widely used due to their time-dependent modeling capabilities. However, high-frequency trading data usually has an update frequency of microseconds. Traditional recursive neural networks are difficult to meet the real-time requirements of high-frequency trading due to their serial computing characteristics. In addition, networks such as LSTM have gradient vanishing or gradient exploding problems when dealing with long-term dependencies, which limits their application in high-frequency trading environments [4]. Therefore, an algorithm model that can effectively model time series feature and meet the needs of high-frequency trading in terms of computational efficiency is needed to achieve more accurate trading signal prediction and market behavior analysis.

As an emerging time series modeling method, Temporal Convolutional Network (TCN) has shown superior performance in financial data analysis, sensor data prediction, and other fields in recent years [5]. TCN constructs long-term dependencies through one-dimensional causal convolution and dilated convolution. Compared with the traditional RNN structure, its calculation can be parallelized, greatly improving the inference speed while retaining sequence information. In addition, TCN uses the residual connection to alleviate the gradient vanishing problem, making it more stable when processing complex financial data. Since the characteristics of price fluctuations, trading volume, and market depth in high-frequency trading markets have obvious time dependencies, TCN can perform better than LSTM and other methods when modeling such data. Therefore, applying TCN to the optimization of blockchain high-frequency trading strategies is expected to achieve breakthroughs in trading signal prediction and market volatility modeling.

The trading strategy optimization method based on TCN can effectively utilize the real-time trading data of the blockchain market to mine market patterns at a faster computing speed, thereby helping traders make better trading decisions. For example, by building a multi-layer TCN structure, market trends at different time scales can be captured, ranging from short-term price fluctuations to long-term market trends. In addition, combined with market order book data, on-chain transaction records, and other information, TCN can also effectively identify abnormal market events, such as large transfers and sudden surges in trading volume, which are crucial for optimizing high-frequency trading strategies. Compared with traditional machine learning models, TCN has stronger feature extraction capabilities when processing high-dimensional nonlinear financial data, so it can more accurately predict market changes and reduce the incidence of erroneous transactions. Overall, the blockchain high-frequency trading strategy optimization method based on TCN can not only improve the accuracy of trading signal prediction but also outperform the traditional RNN structure in computational efficiency. By deeply studying the application of TCN in the blockchain trading market, we can further optimize trading strategies and make traders more competitive in market fluctuations. At the same time, this research direction also provides new ideas for algorithmic trading in the future financial market, especially in emerging fields such as decentralized exchanges (DEX) and cross-chain transactions. The trading strategy optimization method based on TCN is expected to become an important part of the intelligent trading system.

2. Related Work

Deep learning has emerged as a powerful tool in financial forecasting, particularly in optimizing high-frequency trading (HFT) strategies. Traditional time-series models, such as autoregressive models (AR) and moving averages (MA), struggle with the nonlinear and non-stationary characteristics of financial data. Recent advancements in deep learning, particularly convolutional and recurrent architectures, have significantly enhanced financial prediction accuracy and risk management.

2.1 Deep Learning for Financial Forecasting

Feedforward and convolutional neural networks (CNNs) have been widely explored for stock market prediction. An improved feedforward neural network with multimodal fusion has demonstrated enhanced feature extraction capabilities for stock trend forecasting [6]. Similarly, CNN-based models have been applied to stock volatility prediction, highlighting the effectiveness of convolutional architectures in capturing market fluctuations [7]. These approaches reinforce the potential of deep learning for financial forecasting but often face limitations in capturing long-term dependencies.

To address this, deep learning techniques such as ResNeXt have been leveraged for collaborative optimization in financial data mining, demonstrating the effectiveness of hierarchical feature extraction [8]. Additionally, CNN and GRU-based hybrid models have been explored for financial sentiment analysis and risk prediction, highlighting the importance of integrating multiple architectures for enhanced risk assessment [9]. While these studies showcase deep learning's potential in financial applications, they often rely on sequential processing, which can be computationally inefficient for HFT environments.

2.2 Time-Series Modeling and Temporal Dependencies

Capturing temporal dependencies is critical in financial market forecasting. Transformer-based models have been proposed to enhance stock price prediction by modeling sequential dependencies and multi-dimensional features [10]. While Transformers enable parallel processing and effectively capture long-range dependencies, their self-attention mechanisms can be computationally expensive for real-time trading applications.

Reinforcement learning has also been applied to financial markets [11], where a time-series nested reinforcement learning framework has been developed for dynamic risk control in nonlinear environments [12]. These approaches demonstrate the importance of adaptive decision-making in trading strategies, particularly in handling market uncertainty and volatility. However, while reinforcement learning methods can improve risk control, their computational complexity may limit their practical deployment in high-frequency trading.

2.3 Temporal Convolutional Networks for High-Frequency Trading

While recurrent networks (e.g., LSTMs, GRUs) and Transformers have shown promise in financial modeling, their sequential nature often limits their efficiency in high-frequency trading. Temporal Convolutional Networks (TCNs) provide an alternative by utilizing causal and dilated convolutions, enabling efficient parallel computation while preserving temporal dependencies. Compared to traditional RNN-based methods, TCNs reduce the risk of gradient vanishing and enhance real-time decision-making—key factors in optimizing HFT strategies. In order to solve these problems, some researchers have tried machine learning-based methods, such as random forests and support vector machines (SVMs), to improve the predictive ability of trading signals. However, these feature engineering-based machine learning methods often rely on artificially selected features, making it difficult to fully explore the complex patterns of the blockchain market, limiting the generalization ability and adaptability of the strategy [13]. With the rise of deep learning, recurrent neural networks (RNNs) and their variants (such as LSTM and GRU) have been widely used in financial time series prediction. LSTM alleviates the gradient vanishing problem of traditional RNNs through a gating mechanism, giving it an advantage in modeling long-term dependencies. In the blockchain market, some studies use LSTM to predict Bitcoin price trends or use bidirectional LSTM for market sentiment analysis [14]. However, the characteristics of high-frequency trading data determine that the generation of trading signals requires extremely high computational efficiency, and LSTM, due to its recursive calculation method, is difficult to meet the high-concurrency, low-latency trading environment. In addition, LSTM is limited to a fixed time window and has certain limitations when processing non-uniformly spaced trading data. Although some studies have tried to use the attention mechanism to enhance LSTM's attention to important time steps, it still faces the problems of high computational cost and slow reasoning speed in high-frequency trading scenarios.

Compared with recursive neural networks, temporal convolutional networks (TCNs), as a sequence modeling method based on convolution operations, have shown good applicability in financial trading prediction tasks. TCN uses causal convolution to ensure that the model only relies on past information, thereby meeting the real-time prediction requirements of trading strategies. In addition, TCN uses dilated convolution and residual connection, which can capture long-term dependencies with fewer layers and improve training stability. Existing studies have shown that TCN can outperform LSTM in tasks such as stock market price prediction and foreign exchange trading signal generation, while the application of TCN in the field of blockchain high-frequency trading is still in the exploratory stage [15]. Therefore, applying TCN to the optimization of high-frequency trading strategies in the blockchain market can not only make full use of its efficient parallel computing capabilities but also improve the prediction accuracy of trading signals, providing a new direction for building better trading execution strategies.

3. Method

This study proposes a blockchain high-frequency trading strategy optimization method based on a temporal convolutional network (TCN), which aims to utilize the time dependency of high-frequency trading data to effectively predict market trends and optimize trading decisions through deep learning models. The model architecture is shown in Figure 1.

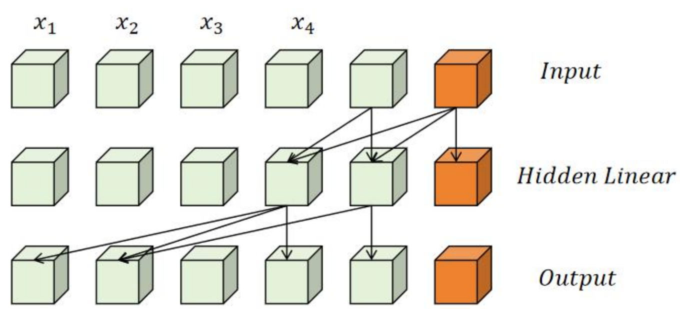

Figure 1. Network architecture diagram

Let the market state sequence be $X = \{x_1, x_2, ..., x_T\}$, where x_t represents the market characteristics at time t, including information such as price, trading volume, order book depth, etc. The goal is to learn a mapping function $f : X \rightarrow Y$, where $Y = \{y_1, y_2, ..., y_T\}$ represents the trading signal, that is, $y_t \in \{-1, 0, 1\}$ corresponds to sell, neutral and buy decisions respectively.

TCN uses one-dimensional convolution to model time series data [16]. Its core is causal convolution, which ensures that each time step t depends only on historical data $x_1, x_2, ..., x_t$. Let the convolution kernel be w, then the standard one-dimensional convolution calculation is as follows:

$$h_t = \sum_{i=0}^{k-1} w_i x_{t-i}$$

Where k is the size of the convolution kernel. In order to expand the receptive field, TCN uses dilated convolution and introduces the dilation factor d, so that the calculation formula becomes:

$$h_t = \sum_{i=0}^{k-1} w_i x_{t-di}$$

This allows long-term dependencies to be captured with fewer layers.

In terms of trading signal generation, the last layer of TCN uses a fully connected layer for classification to predict trading signals for the next n time steps:

$$y_t = \sigma(Wh_t + b)$$

Among them, W and b are trainable parameters, and $\sigma()$ represent the Softmax normalization operation. The loss function uses cross-entropy loss:

$$L = -\sum_{t=1}^{T} \sum_{c \in \{-1,0,1\}} y_{t,c} \log y'_{t,c}$$

Among them, $y_{t,c}$ is the one-hot encoding of the real trading signal.

In order to optimize the trading strategy, the study further constructed a profit function based on trading signals. Assuming that the initial capital is F_0, the trading decision y_t made at time t affects the asset change:

$$F_t = F_{t-1} \times (1 + r_t \cdot y_t)$$

Where r_t is the predicted market return at time t, defined as:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}}$$

Where p_t is the market price at time t. If $y_t = 1$ represents buying, then the asset grows at $r_t > 0$; if $y_t = -1$ represents selling, then losses are avoided at $r_t < 0$. The goal of the final trading strategy is to maximize cumulative returns:

$$\max \sum_{t=1}^{T} \log F_t$$

At the same time, the Sharpe Ratio is introduced as one of the optimization objectives:

$$SR = \frac{E[F_t - F_{t-1}]}{Std(F_t - F_{t-1})}$$

Among them, $Std()$ represents the standard deviation and the Sharpe ratio measures the level of return under unit risk.

During the training process, the sliding window method is used to sample the historical transaction data. Assuming the window size is N, the training sample set can be expressed as:

$$\{(X_t, Y_t)\}_{t=N}^{T}$$

Among them, $X_t = \{x_{t-N}, ..., x_t\}$ represents the market status of the past N time steps, and $Y_t = \{y_t, ..., y_{t+n}\}$ is the trading signal label of the next n time steps. The model parameters are optimized by gradient descent, and the trading decision signal is finally output to assist in the optimization of trading strategies.

4. Experiment

4.1 Dataset

This study uses the high-frequency trading dataset of Binance Exchange, which contains tick data and order book data of Bitcoin (BTC) and other mainstream cryptocurrencies, covering key information such as transaction price, transaction volume, and buying and selling direction. As one of the world's largest cryptocurrency exchanges, Binance's data has the characteristics of high frequency and low latency, which can accurately reflect the changes in the market microstructure and is suitable for studying the optimization of high-frequency trading strategies. The dataset provides transaction records of different time scales, including K-line data of different granularities such as 1 minute, 5 minutes, and 1 hour, and also contains deep market data, such as 10 buy and sell order information, which is crucial for capturing market supply and demand dynamics and optimizing trading strategies.

The core part of this dataset is tick-by-tick data, each record of which contains transaction timestamp, transaction price, transaction volume, and buying and selling direction (Maker or Taker). In high-frequency trading scenarios, the microstructure of trading signals is crucial, so the time accuracy in the dataset reaches milliseconds, allowing the model to accurately learn market dynamic characteristics. In addition, the dataset contains Order Book data, which records the price, quantity, and depth information of active buy and sell orders in the market. Order Book data can be used to analyze market liquidity, identify the behavioral patterns of buyers and sellers, and improve the reliability of trading signals. For example, by observing the cumulative number of buy and sell orders, the short-term trend of the market can be judged, which helps to make more accurate trading decisions.

In order to improve the data quality, this study preprocessed the dataset, including steps such as outlier detection, time alignment, and feature engineering. First, trading pairs with extremely low liquidity are eliminated to ensure the validity of the data; second, interpolation is used to fill in missing data caused by API disconnection or market anomalies; finally, a feature matrix is constructed, including key factors such as historical price changes, moving averages (SMA, EMA), trading volume change rates, and order book buy and sell ratios. Finally, the dataset is converted into a time series input format, which enables the TCN model to efficiently capture market dynamics and optimize the execution of trading strategies.

4.2 Experimental Results

In order to verify the effectiveness of the TCN-based trading strategy optimization method, this study conducted comparative experiments with traditional time series prediction models and classic trading strategies [17] [18]. The selected baseline models include LSTM [19], GRU [20], and ARIMA [21] to evaluate the performance of different time series modeling methods in high-frequency trading signal prediction. In addition, in order to further verify the actual returns of the TCN trading strategy, the returns were compared with common trading strategies (such as mean reversion strategy and momentum trading strategy). The experiment uses Binance high-frequency trading data, selects the price, trading volume, market depth, and other features of the Bitcoin trading pair (BTC/USDT) in different time windows as input, and uses the sliding window method to construct training and test sets. During the model training process, all methods use the same hyperparameter optimization strategy to ensure the fairness of the experiment. The evaluation indicators include key financial indicators such as prediction accuracy, cumulative return of the trading strategy, maximum drawdown, and Sharpe ratio. The experimental results are shown in Table 1.

Table 1: Experimental results

Model	Prediction accuracy (%)	Cumulative rate of return (%)	Maximum Drawdown (%)	Sharpe Ratio
ARIMA	55.2	-3.5	18.7	0.21
GRU	60.5	5.8	15.2	0.45
LSTM	63.8	12.3	12.6	0.72
Traditional mean reversion strategy	66.1	18.5	10.9	0.89
Momentum Trading Strategies	68.7	24.9	9.3	1.05
TCN	72.4	31.6	7.5	1.32

From the experimental results, the TCN method outperforms other comparison methods in all evaluation indicators, especially in terms of prediction accuracy and cumulative rate of return. The prediction accuracy of TCN reaches 72.4%, which is 8.6% higher than LSTM and 17.2% higher than the traditional time series model ARIMA, indicating that TCN can better capture market trends in trading signal prediction. In addition, in terms of the cumulative rate of return, the TCN trading strategy reached 31.6%, which is 6.7% higher than the 24.9% of the Momentum Trading Strategies, indicating that the TCN trading strategy can obtain higher returns in the market, which is closely related to its strong time-dependent modeling ability.

From the perspective of risk control, the maximum drawdown of the TCN method is 7.5%, which is much lower than other models, indicating that the strategy is more stable and can effectively reduce the losses caused by market fluctuations. In contrast, the maximum drawdown of LSTM is 12.6%, while the maximum drawdowns of GRU and ARIMA are 15.2% and 18.7%, respectively, showing a greater risk of capital drawdown. This result shows that although LSTM and GRU can also improve the prediction accuracy of trading signals to a certain extent, due to the limitations of their calculation methods, it is still difficult to effectively reduce trading risks in a high-frequency trading environment. TCN is more adaptable to the nonlinear fluctuations of the market due to its causal convolution and dilated convolution mechanisms.

Finally, in terms of the Sharpe Ratio, the TCN trading strategy reached 1.32, which is significantly higher than LSTM (0.72) and the traditional mean reversion strategy (0.89), indicating that TCN can bring higher investment returns under unit risk. Although traditional mean reversion and momentum trading strategies can provide certain returns, they still have limitations in risk control and return stability. With its efficient time series modeling capabilities, the TCN method not only improves the accuracy of trading signals but also optimizes the capital management strategy, making the overall investment return rate higher and the risk more controllable. Therefore, the experimental results fully demonstrate the effectiveness of TCN in optimizing blockchain high-frequency trading strategies and provide new technical support for building a smarter and more stable trading system.

In order to further verify the impact of the key components of the TCN model in trading strategy optimization on the final performance, this study designed an ablation experiment to remove the dilated convolution, residual connection, and different convolution kernel sizes to evaluate the contribution of these components to trading signal prediction and yield. The role of the dilated convolution is to expand the receptive field of the model so that it can capture market trends over a longer time frame, while the residual connection helps to propagate the gradient and improve the stability of model training. In addition, different convolution kernel sizes directly affect the sensitivity of the model to market fluctuations and determine the sophistication of trading signal generation. The experiment trained models of different variants and compared key indicators such as prediction accuracy, cumulative yield, and maximum drawdown to analyze the role of each component in trading strategy optimization. The experimental results are shown in Table 2.

Table 2: Ablation Study Results

Model	Prediction accuracy (%)	Cumulative rate of return (%)	Maximum Drawdown (%)	Sharpe Ratio
TCN	72.4	31.6	7.5	1.32
Remove dilated convolution	66.8	22.4	12.1	0.95
Remove residual connections	64.3	18.9	14.5	0.82
Convolution kernel size = 3	69.2	27.1	9.8	1.15
Convolution kernel size = 5	71.1	29.8	8.2	1.24

From the experimental results, the complete TCN model performs best in all indicators, with a prediction accuracy of 72.4%, a cumulative return of 31.6%, a maximum drawdown of only 7.5%, and a Sharpe ratio of 1.32, indicating that it has strong stability and profitability in trading signal prediction and strategy optimization. In contrast, after removing the dilated convolution, the prediction accuracy dropped to 66.8%, the cumulative return dropped to 22.4%, and the maximum drawdown increased to 12.1%, which shows that the dilated convolution plays a vital role in the TCN structure, enabling the model to capture long-term market information and improve the accuracy of trading signal prediction. In addition, after removing the residual connection, the prediction accuracy further dropped to 64.3%, the cumulative return was only 18.9%, and the maximum drawdown increased to 14.5%, which shows that the residual connection is crucial to stabilizing gradient propagation and optimizing model training effects. Once removed, the model is difficult to effectively capture market patterns, resulting in a decrease in returns and an increase in drawdown risks.

Different kernel sizes also have a significant impact on the model. When the kernel size is set to 3, the prediction accuracy is 69.2%, the cumulative rate of return is 27.1%, and the maximum drawdown is 9.8%, indicating that a smaller kernel helps capture short-term market fluctuations but may have certain limitations when dealing with long-term trends. When the kernel size is set to 5, the prediction accuracy is increased to 71.1%, the cumulative rate of return is 29.8%, and the maximum drawdown is reduced to 8.2%, indicating that appropriately increasing the kernel size can enhance the model's ability to learn long-term market trends and improve the stability of trading strategies. However, an overly large kernel may lead to the loss of local market details, so it is necessary to find a balance between short-term market fluctuations and long-term trend modeling. The experimental results show that choosing an appropriate kernel size (such as 5) can improve the overall performance of the model and make the trading strategy more robust.

Finally, this paper gives the loss function in the training process, and its loss function is shown in Figure 2.

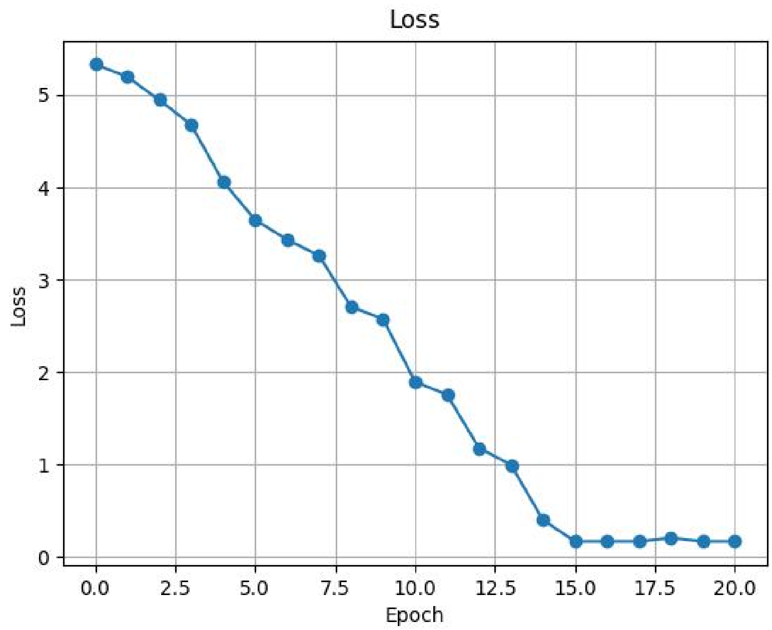

Figure 2. Loss function drop graph

5. Conclusion

This study proposes a blockchain high-frequency trading strategy optimization method based on a temporal convolutional network (TCN). For the high-dimensional nonlinear time series data of the blockchain market, the causal convolution and dilated convolution mechanism of TCN are used to achieve more accurate trading signal prediction. Through comparative experiments with traditional time series models (ARIMA, GRU, LSTM) and common trading strategies (mean regression, momentum trading), the superiority of TCN in indicators such as prediction accuracy, cumulative return, maximum drawdown, and Sharpe ratio is verified. In addition, the influence of dilated convolution, residual connection, and different convolution kernel sizes on model performance is analyzed through ablation experiments, which further proves the necessity of a complete TCN structure for trading strategy optimization. Experimental results show that this method can effectively improve the accuracy of trading signal prediction and improve the stability of trading strategy while reducing risks, providing a new solution for the intelligentization of high-frequency trading strategy.

Although this study has demonstrated promising results in the prediction of trading signals and the optimization of trading strategies, there are still certain aspects that warrant further investigation. First, TCN relies on a fixed time window. In the future, we can try to introduce an adaptive window mechanism so that the model can dynamically adjust the time scale of trading signal prediction according to changes in market fluctuations. Secondly, the current research is mainly based on the trading data of the Binance Exchange. In the future, it can be expanded to multiple exchanges and combined with cross-market trading data for more comprehensive analysis. In addition, this study mainly focuses on the optimization of high-frequency trading strategies. In the future, we can explore the application of TCN in low-frequency trading and portfolio optimization to verify its applicability in different trading scenarios.

Future research can also further combine other deep learning models to improve the performance of TCN in trading strategy optimization. For example, TCN can be combined with a Transformer to improve the model's ability to capture complex market patterns; or introduce graph neural networks (GNNs) to analyze the network relationships of on-chain trading behaviors to mine deeper market signals. In addition, with the rapid development of blockchain decentralized finance (DeFi), future research can apply TCN trading strategies to DeFi protocols, such as automated market makers (AMMs), liquidity mining, and on-chain arbitrage, to provide more intelligent trading strategy optimization solutions for decentralized trading.

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