Stock Price Prediction Based on Phase Space Reconstruction and TCN

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Abstract: To address the issue of stock prices exhibiting complex nonlinear characteristics due to the combined influence of multiple factors, which makes accurate prediction difficult using traditional statistical methods, this paper proposes a predictive model integrating Phase Space Reconstruction (PSR), an attention mechanism, and a Temporal Convolutional Network (PSR-ATT-TCN). First, multidimensional variables undergo PSR processing to obtain input variables. Subsequently, an attention mechanism determines the weight coefficients of each input variable. The Temporal Convolutional Network (TCN) then captures long-term dependency information to establish the price prediction model. Experimental results demonstrate that the PSR-ATT-TCN model achieves smaller errors in MAE, MSE, and RMSE metrics, exhibiting enhanced prediction accuracy and generalization performance.

Keywords: Stock Price Prediction; Phase Space Reconstruction; Temporal Convolutional Network; Attention Mechanism

1. Introduction

From the overall situation of domestic and foreign stock markets, it is often difficult to accurately grasp the law of its operation and changes. Especially for stock price data with nonlinear characteristics, the construction of scientific and effective prediction models can provide a new exploration direction for relevant researchers. Due to the significant nonlinear characteristics of stock price data, the construction of effective prediction models has become a key breakthrough in this field. In fact, scholars have confirmed the chaotic properties of stock price fluctuations by calculating the maximum Lyapunov index[1-4]. Chaos theory is also widely used in other fields, especially in prediction [5][6].

In recent years, the application of deep learning models in the field of stock price prediction has become more and more common, thanks to their powerful learning capabilities and high simulation performance. As an efficient deep learning architecture, Time Convolutional Networks (TCNs) have demonstrated excellent prediction performance in various fields such as clinical research, environmental monitoring, meteorological analysis, and power systems. Jining Yan (2020) used the EEMD-TCN hybrid method to predict the El Niño-Southern Oscillation (ENSO) phenomenon[7]. Bryan P. Bednarski (2022) discusses in detail the application of TCN in clinical length and mortality prediction[8], demonstrating its superior performance compared to traditional models. Xiaoyan Wei (2023) used a model of TCN and LSTM combined with attention mechanisms to predict carbon emissions[9], improving the accuracy and interpretability of the model for long-sequence data processing. Wenlin Li (2023) demonstrated the effectiveness of TCN in predicting air pollutant concentrations[10]. A number of research results show that the integration of time convolutional network (TCN) with other technologies can not only effectively process complex time series data, but also significantly improve prediction accuracy and computational efficiency in many fields. Zhang et al. (2024) used a model that integrates TCN and LSTM with emotional characteristics to predict stock prices, which can effectively improve prediction accuracy compared to other models[11].

Based on the above analysis, this paper constructs a stock closing price prediction model that combines phase space reconstruction technology, attention mechanism and temporal convolutional neural network (TCN). Specifically, the phase space reconstruction method is used to process the variables of each dimension, and the one-dimensional time series is mapped to the high-dimensional space, so as to deeply explore the time-dependent characteristics of the variables and improve the prediction accuracy of the model. Then, the weight coefficient and optimal hyperparameters of TCN input variables are determined to construct a more accurate prediction model architecture. The results show that the model has higher prediction accuracy and generalization ability, which fully confirms the feasibility and effectiveness of the model.

2. Introduction to Algorithms

2.1 Phase Space Reconstruction

2.1.1 Phase space reconstruction

The core purpose of the phase space reconstruction method is to map the data to the high-dimensional phase space, so as to deeply analyze the structural characteristics and dynamic laws of the system. This method has a wide range of application value in the fields of complex system research, chaotic dynamics analysis, and nonlinear time series processing.

For the M-dimensional time series of dynamic systems with chaotic characteristics, $X=[X_1(t), X_2(t), X_3(t), \cdots X_M(t)]$, the phase space reconstruction can be realized after determining the delay time τ and the optimal embedding dimension m of each variable, and the reconstruction results are as follows:

$$\begin{aligned} \boldsymbol{X}' = [&X_1(t),\ X_1(t-\tau_1)\cdots,\ X_1(t-(m_1-1)\tau_1), \\ &X_2(t),\ X_2(t-\tau_2),\ \cdots,\ X_2(t-(m_2-1)\tau_2), \\ &X_M(t),\ X_M(t-\tau_M),\ \cdots,\ X_M(t-(m_M-1)\tau_M)] \end{aligned} \quad (1)$$

where $\boldsymbol{X}'$ represents the reconstructed time series, $\tau_1 \ldots \tau_M$ represents the delay time of each dimensional variable, and $m_1 \ldots m_M$ represents the optimal embedding dimension of each dimensional variable.

2.1.2 Parameter selection

To reconstruct the phase space of a multidimensional feature of an equity system, we must first determine its delay time τ with the embedding dimension m. In this paper, the mutual information method is used to determine the time delay τ, and the CAO method is used to determine the embedding dimension m.

(1) The basic principles of the mutual information method are as follows:

First, let's introduce entropy, if the discrete variables X and Y correspond to the number of states a, b, then the information entropy corresponding to the variables X and Y is:

$$H(X) = -\sum_{i=1}^{a} p_i \log p_i \quad (2)$$

$$H(Y) = -\sum_{j=1}^{b} p_j \log p_j \quad (3)$$

Where p_i is the probability when the variable X is in state i, p_j is the probability when the variable Y appears in state j.

Define the joint entropy $H(X,Y)$ of the two variables:

$$H(X,Y) = -\sum_{i=1}^{a}\sum_{j=1}^{b} p_{ij} \log p_{ij} \quad (4)$$

where p_{ij} represents the joint probability that the variable X is state i and the variable Y is state j.

Mutual information for two variables is defined as:

$$I(X,Y) = H(X) + H(X) - H(X,Y) \quad (5)$$

For more general cases, in multivariate, the mutual information is:

$$I_0(X_0,\cdots X_n) = \sum_j \left[H(X_j) - H(X_0,\cdots X_n)\right] \quad (6)$$

The time corresponding to the first time when $I_n(T)$ reaches the minimum value is the delay time.

(2) Cao method

Embedding the time series $\{x_i\}_{i=1}^{N}$ into the phase space of the m dimension yields:

$$X_i(m) = \{x_i, x_{i+\tau}, \cdots, x_{i+(m-1)\tau}\} \quad (7)$$

where N is the length of the data volume, and τ is the delay time.

Definition $E_1(m)$:

$$E_1(m) = E(m+1)/E(m) \quad (8)$$

$$E(m) = \frac{1}{N-m\tau}\sum_{i=1}^{N-m\tau} \frac{\|X_{m+1}(i) - X_{m+1}(n(i,m))\|}{\|X_m(i) - X_m(n(i,m))\|} \quad (9)$$

where N represents the number of samples, $\|\cdot\|$ represents the absolute distance, $X_m(i)$ represents the i-th vector in the reconstructed m-dimensional phase space, and $X_m(n(i,m))$ is the closest point of the vector $X_m(i)$ in the m dimensional phase space.

When $E_1(m)$ tends to be saturated, it means that the space orbit has fully expanded and there are no more false proximity points. Therefore, the dimension corresponding to the saturation of $E_1(m)$ is the embedding dimension m.

2.2 Attention Mechanism

In this paper, an attention mechanism is added to the input layer of the network to give weight to the reconstructed variables.

Assuming that the input sequence is $X=(x_1, x_2, \cdots, x_n)$ and n is the length of the time series, the calculation steps of the attention mechanism are as follows:

Step 1: Initialize the q and k variables of the input sequence $X=(x_1,x_2,\cdots,x_n)$, and use Equation (10) to calculate the attention score.

$$s(x_n,q)=\frac{q\cdot k}{\sqrt{d_k}} \quad (10)$$

where q is the query vector; k is the key vector; d_k is the key vector dimension; $s(x_n,q)$ is a scoring function, which is used to represent the correlation between query features and query vectors.

Step 2: Normalize the attention score calculated in Step 1 by the Softmax function to obtain the weight coefficient a_i of the attention value, and the calculation formula is shown in Equation (11).

$$a_i=Softmax\big(s(x_i,q)\big)=\frac{\exp\big(s(x_i,q)\big)}{\sum_{j=1}^{N}\exp\big(s(x_j,q)\big)} \quad (11)$$

Step 3: Weighted sum the calculated attention value vector v_i with the corresponding weight coefficient to obtain the final output, and the calculation formula is shown in Equation (12).

$$Attention(v)=T\sum_{i=1} a_i\, v_i \quad (12)$$

where $Attention(v)$ is the output of the attention mechanism; a_i is the attention weight of the i-th element; v_i is the attention value vector of the i-th element.

2.3 Temporal Convolutional Network

Temporal Convolutional Network (TCN) is an improved temporal modeling architecture based on one-dimensional convolutional neural networks. As shown in Figure1, its core structure adopts a multi-layer stacked causal convolutional layer, which effectively avoids the problem of future information leakage in the prediction process by strictly limiting the receptive field in the time dimension (the output of T at each time point only depends on the input at T moment and before). This design allows the network to handle variable-length input sequences and keep input and output lengths consistent, with causal convolution operations expressed as:

$$F(s)=\sum_{i=0}^{k\text{-}1}f(i)x_{s\text{-}di} \quad (13)$$

where x is the input, f is the filter, d is the expansion factor, k is the convolutional kernel size, and $x_{s\text{-}di}$determines that only the past input data is convoluted.

3. Stock Closing Price Prediction Based on PSR-ATT-TCN

Due to the typical chaotic nature of stock price fluctuations, traditional direct prediction methods are often difficult to effectively capture their internal evolution laws. According to its chaotic characteristics, the high-dimensional dynamic law is extracted through phase space reconstruction, and the time convolutional network (TCN) is optimized with the attention mechanism to achieve accurate capture and prediction of temporal features, and the prediction framework is shown in Figure 2.

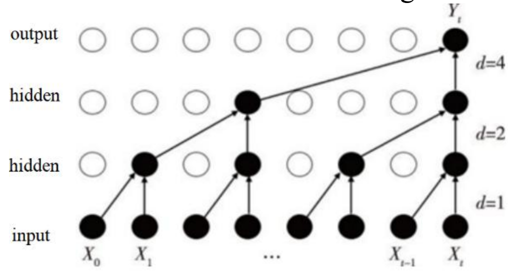

Figure 1. Schematic Diagram of Causal Convolution

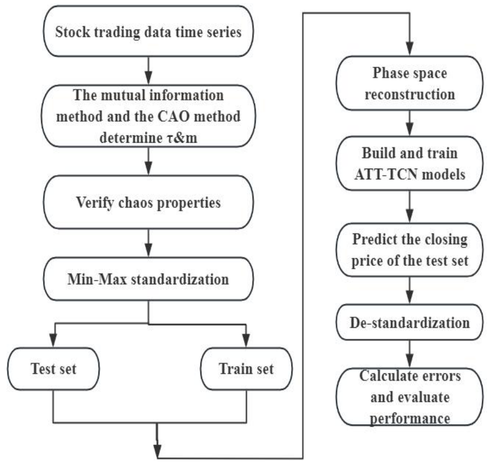

Figure 2. Stock Price Prediction Framework

3.1 PSR-ATT-TCN Stock Closing Price Prediction Process

1) Extract the historical trading data of the stock and construct a multivariate time series of stock closing price prediction.

2) The delay time of each time series is measured by the mutual information method, and the embedding dimension is solved by the Cao method, so as to obtain the reconstructed multivariate time series, so as to clarify the input and output characteristics of the model.

3) The datasets is divided into two parts: training and test datasets, and after the data normalization operation, the time series feature weight allocation of TCN is optimized by attention mechanism (ATT), and the TCN prediction model is trained with training samples.

4) Input the test datasets into the trained prediction model, output the prediction results, and evaluate the effect accordingly.

3.2 Prediction and Evaluation Indicators

In order to scientifically evaluate the prediction accuracy, a systematic evaluation index system is constructed to verify the effectiveness of the proposed model and realize the quantitative comparison of the prediction performance of different algorithms. The evaluation indicators are as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i\text{-}\widehat{y}_i)^2} \tag{14}$$

$$MAE=\frac{1}{n}\sum_{i=1}^{n}|y_i\text{-}\widehat{y}_i| \tag{15}$$

where y_i and $\widehat{y}_i$ represent the true value and the predicted value, respectively.

4. Experimental Results and Analysis

4.1 Stock Dataset Construction

In order to ensure the representativeness of the sample, this paper takes the constituent stocks of the CSI 300, the benchmark index of China's A-share market, as the research object, and selects 12 stocks from 4 different industries for analysis, and the time range of data selection is from January 1, 2015 to January 1, 2025, and the price indicator data include: opening price, closing price (close), high price, low price (low) and volume (volume). The data source is Oriental Fortune. The specific stocks selected are shown in Table 1:

Table 1. Stocks Selected for the Experiment

Category	Ticker symbol	Stock name	Ticker symbol	Stock name	Ticker symbol	Stock name
Bank	SH601398	ICBC	SH600036	CMB	SH601988	BOC
Liquor	SH600519	Kweichow Moutai	SZ000858	Wuliangye	SZ002304	Yanghe Co.,Ltd
Automobile	SZ002594	BYD	SH600104	SAIC	SZ000625	Changan Automobile

4.2 Phase Space Reconstruction Parameter Estimation

The delay time and phase space dimension of each characteristic time series were determined according to the mutual information method and the CAO method, and then the maximum Lyapunov exponent calculated by the Wolf method was used, and the index greater than 0 indicated that the characteristic time series had chaotic properties, and the parameter estimation results were shown in Table 2-Table 4.

Table 2. Results of Bank Phase Space Reconstruction

Name	ICBC			CMB			BOC		
	τ	m	λ	τ	m	λ	τ	m	λ
close	12	4	0.0047	12	4	0.0051	19	4	0.0043
open	26	5	0.0004	17	7	0.0007	24	3	0.0014
high	20	4	0.0017	19	5	0.0014	21	3	0.0025
low	13	4	0.0065	14	4	0.0040	16	4	0.0035
volume	13	4	0.0074	12	4	0.0051	20	4	0.0014

The analysis of the results in the table shows that the delay time of different stock price indicators varies greatly, and the embedding dimension of most price indicators is 4 dimensions, indicating that there is still a certain gap in the characteristics of the price index series between different stocks, and there are differences in trend pattern and internal structure.

At the same time, the maximum Lyapunov index calculated by the price indicators of different stocks is greater than 0, that is, the price index series of each stock is chaotic and is a chaotic time series, and the phase space reconstruction method is mainly applied to the chaotic time series, which verifies the rationality and effectiveness of phase space reconstruction of the price series to predict stock prices.

Table 3. Results of Spatial Reconstruction of Liquor Phase

Name	Kweichow Moutai			Wuliangye			Yanghe Co.,Ltd		
	τ	m	λ	τ	m	λ	τ	m	λ
close	18	5	0.0019	18	4	0.0029	18	3	0.0042
open	11	6	0.0023	26	4	0.0017	22	4	0.0037
high	15	5	0.0018	14	5	0.0022	14	3	0.0045
low	17	5	0.0019	19	4	0.0030	16	4	0.0044
volume	11	4	0.0074	8	4	0.0060	14	4	0.0058

Table 4. Results of Spatial Reconstruction of Automotive Phases

Name	BYD			SAIC			Changan Automobile		
	τ	m	λ	τ	m	λ	τ	m	λ
close	26	4	0.0014	17	6	0.0041	15	4	0.0022
open	26	5	0.0020	17	4	0.0035	22	5	0.0008
high	18	5	0.0010	16	4	0.0041	16	4	0.0021
low	19	4	0.0031	24	4	0.0013	26	6	0.0005
volume	9	4	0.0126	18	3	0.0066	8	4	0.0154

4.3 Analysis of Prediction Results

4.3.1 Ablation experiment

In order to verify the contribution of each key module in PSR-ATT-TCN to the model performance，an ablation experiment containing multiple sub-module combinations is designed, and phase space reconstruction and attention mechanism components are gradually introduced，and their performance is quantitatively evaluated. The specific model settings are as follows:

1) TCN: Foundation model, using only standard TCN structures for sequence modeling;
2) PSR TCN: Introduce PSR on the basis of the TCN model;
3) ATT-TCN: Introduction of attention mechanism on the basis of TCN model;
4) PSR-ATT -TCN: This is the complete model proposed in this paper, which integrates the TCN architecture of PSR and ATT. The ablation results are shown in Table 5-7:

Table 5. Bank Ablation Experimental Results

Method	ICBC			CMB			BOC		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
TCN	0.093	0.016	0.127	0.932	1.456	1.207	0.163	0.040	0.198
PSR+TCN	0.083	0.012	0.109	0.507	0.474	0.688	0.107	0.018	0.136
ATT+TCN	0.076	0.009	0.094	0.563	0.556	0.745	0.198	0.051	0.225
PSR-ATT -TCN	0.069	0.008	0.093	0.459	0.356	0.597	0.082	0.012	0.111

Table 6. Experimental Results of Liquor Ablation

Method	Kweichow Moutai			Wuliangye			Yanghe Co.,Ltd		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
TCN	64.511	6575.132	81.087	9.577	121.99	11.045	4.582	31.863	5.645
PSR+TCN	31.519	1677.668	40.959	3.872	21.461	4.633	3.135	14.677	3.831
ATT+TCN	50.715	3426.810	58.539	12.098	157.817	12.563	3.893	23.826	4.881
PSR-TCN-ATT	23.881	1004.103	31.688	2.403	11.840	3.441	3.011	12.224	3.496

Table 7. Results of Automobile Ablation Experiments

Method	BYD			SAIC			Changan Automobile		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
TCN	9.215	151.039	12.289	0.858	1.103	1.050	0.881	1.114	1.056
PSR+TCN	**5.192**	**40.453**	**6.360**	0.937	0.944	0.972	0.552	0.479	0.692
ATT+TCN	6.403	65.809	8.112	0.966	1.433	1.197	0.623	0.787	0.887
PSR-ATT -TCN	**5.037**	**40.674**	**6.378**	0.769	0.809	0.893	0.381	0.271	0.5202

In Table 5-7, the models are compared and evaluated from three dimensions: MAE, MSE and RMSE on three different types of datasets: bank, liquor and automobile. Taking the three datasets of Bank of China, Kweichow Moutai and BYD as examples, compared with the basic TCN, the MAE of PSR-ATT-TCN on the Bank of China dataset decreased from 0.1628 to 0.0819, a decrease of 49.7%. RMSE fell from 0.1984 to 0.1114, a decrease of 43.9%. On the Kweichow Moutai dataset, the MAE of PSR-ATT-TCN dropped from 64.5107 to 23.8806, with a 63.0% error reduction and a 60.9% RMSE decrease. On the BYD dataset, PSR-ATT-TCN's MAE decreased from 9.2152 to 5.0367, and RMSE decreased from 12.2898 to 6.3776, down 45.3% and 48.1% respectively.

Furthermore, compared with the PSR-TCN structure with only PSR, the MAE of PSR-ATT-TCN was reduced to varying degrees, indicating that the attention mechanism has a good role in weighting features and improving the key timing modeling effect. In addition, compared with the ATT-TCN model with ATT alone, the performance of PSR-ATT-TCN is also better, indicating that the phase space reconstruction improves the model's ability to understand the dynamic characteristics of the system by mining the temporal feature information, and has a good effect on improving the accuracy of model prediction.

4.3.2 Comparison experiments

In this paper, two representative time series prediction models are selected for comparison experiments. Including: CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory Network). All models are trained and evaluated under the same input characteristics, data division and training hyperparameter settings, and the performance comparison is uniformly based on three indicators: MAE, MSE and RMSE. The experimental results are shown in Table 8-10.

The table shows the comparison results of the prediction performance of each dataset. Overall, the PSR-ATT-TCN model achieves the best or near-optimal performance in MAE, MSE and RMSE indicators on all datasets, showing stronger predictive ability and robustness than CNN and LSTM methods.

In the Bank of China dataset, the RMSE of PSR-ATT-TCN is 0.1114, which is 24.0% lower than that of LSTM (0.1466) and 10.9% lower than that of CNN (0.1251). On Kweichow Moutai data, the MAE of PSR-ATT-TCN is 23.8806, down 69.0% from LSTM (77.1474) and 64.5% from CNN (67.3566). In the BYD dataset, the MAE and RMSE of PSR-ATT-TCN were 5.0367 and 6.7336, respectively, which were 46.4% and 43.5% lower than LSTM, and 35.9% and 35.1% lower than CNN, respectively. The above results show that PSR-ATT-TCN has a good effect on improving the prediction accuracy and generalization ability of the model.

Table 8. Bank Comparison Experiment Results

Method	ICBC			CMB			BOC		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
LSTM	0.071	0.009	0.096	0.947	1.253	1.119	0.113	0.022	0.147
CNN	0.099	0.018	0.133	0.626	0.671	0.818	0.089	0.016	0.125
PSR-ATT-TCN	0.069	0.008	0.093	0.459	0.356	0.597	0.082	0.012	0.111

Table 9. Liquor Comparison Experimental Results

Method	Kweichow Moutai			Wuliangye			Yanghe Co.,Ltd		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
LSTM	77.147	7675.102	87.608	7.999	88.139	9.388	3.505	18.509	4.302
CNN	67.357	5899.197	76.806	5.532	44.447	6.667	2.523	13.474	3.671
PSR-ATT-TCN	23.881	1004.103	31.688	2.403	11.841	3.441	3.011	12.224	3.496

Table 10. Results of Automobile Comparison Experiments

Method	BYD			SAIC			Changan Automobile		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
LSTM	9.392	127.249	11.281	0.953	1.392	1.179	0.873	1.209	1.099
CNN	7.864	96.506	9.824	0.983	1.418	1.191	0.612	0.632	0.795
PSR-ATT-TCN	5.037	40.674	6.378	0.769	0.809	0.893	0.381	0.271	0.520

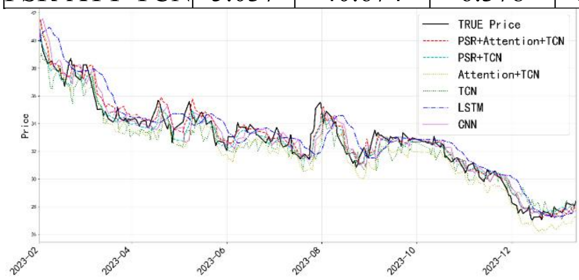

Figure 3. The First Half of the Forecast Stock Price Performance Chart

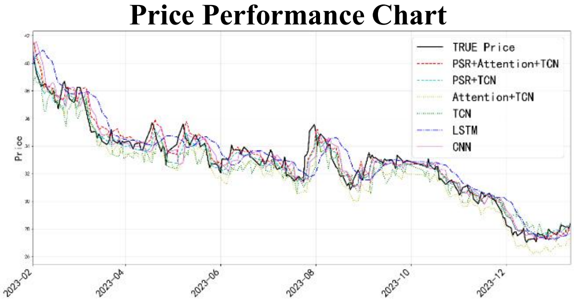

Figure 4. The Second Half of the Forecast Stock Price Performance Chart

In order to further verify the performance of the model in the actual prediction task, the visual prediction results of the China Merchants Bank dataset are plotted, as shown in Figure3 and Figure4. The red curve in the figure3&4 is the predicted value of the PSR-ATT-TCN model, and the black curve is the real stock price. It can be observed from the figure that in most time periods, the prediction curve is highly consistent with the overall trend of the real trend, and the model can effectively capture its long-term trend and respond reasonably to local short-term fluctuations, reflecting good time series modeling capabilities. At the same time, there are obvious differences in the fitting effect of different models, and the PSR-ATT-TCN model proposed in this paper maintains a high consistency with the real value in most intervals, showing a more accurate characterization of the financial time series fluctuation law.

5. Conclusion

In this paper, a time convolutional neural network (PSR-ATT-TCN) model with a fusion phase spatial reconstruction-attention mechanism is proposed to address the challenges of nonlinearity, dynamic complexity and uncertainty in the field of stock market price prediction.

By constructing a phase space reconstruction

(PSR)-attention mechanism (ATT)-time convolutional neural network (TCN), the TCN model effectively overcomes the shortcomings of capturing complex nonlinear relationships and spatial dynamics between features, and significantly improves the modeling ability of stock price fluctuation features. Through experimental research in three different industries: banking, liquor and automobiles, the TCN, LSTM, CNN model, and PSR-ATT-TCN model show obvious advantages in key evaluation indicators such as MAE, MSE and RMSE, which proves the prediction ability and generalization performance of the proposed method in actual financial scenarios. In addition, the necessity and effectiveness of phase space reconstruction and attention mechanism for model performance improvement are further verified by ablation experiments.

In summary, the PSR-ATT-TCN model effectively enhances the feature expression ability of the model through the integration of phase space reconstruction and attention mechanism, more accurately depicts the nonlinear evolution law of stock prices, and provides reliable technical support for stock market prediction analysis and investment decisions. Future research directions include introducing more macroeconomic and policy factors to further improve the prediction accuracy of the model, enhance the interpretability of the model, and expand its application in more financial field.

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