Journal of computer science and software applications
https://www.mfacademia.org/index.php/jcssa
ISSN:2377–0430
Vol. 5, No. 2, 2025

Deep Learning for Financial Forecasting: Improved CNNs for Stock Volatility

Jinsong Liu
University at Buffalo, Buffalo, USA
jinsongl@buffalo.edu

Abstract:

This study proposes a stock price volatility prediction model based on an improved convolutional neural network (CNN) to improve the accuracy of stock market volatility prediction. By introducing the characteristics of convolutional neural networks, this study can automatically extract multi-level features when processing stock market data and effectively capture the complex patterns in stock price fluctuations. Compared with traditional machine learning models such as support vector machines (SVM) and random forests (RF), and deep learning models such as long short-term memory networks (LSTM), the improved CNN model shows lower mean square error (MSE), mean absolute error (MAE) and root mean square error (RMSE) in the stock price volatility prediction task, showing a more significant advantage. Through experimental verification of European stock market data from 2010 to 2023, the results show that the improved CNN model not only surpasses other comparison models in accuracy but also has strong adaptability and stability. Future research can further explore the combination of other deep learning technologies with CNN to improve the prediction ability of the model while considering the introduction of more external economic factors and multimodal data to provide more accurate decision support for stock market prediction.

Keywords:

Stock price volatility, Convolutional Neural Networks (CNN), Stock market prediction, Deep learning

1. Introduction

Stock market volatility is an important indicator for measuring the fluctuation range of stock prices. It is widely used in financial risk management, portfolio optimization, and derivative pricing. With the increasing complexity of global financial markets, accurately predicting stock price volatility has become an important challenge for investors and researchers [1]. Traditional stock price volatility prediction methods are mostly based on statistical models of historical data, such as ARCH (autoregressive conditional heteroskedasticity model) and GARCH (generalized autoregressive conditional heteroskedasticity model) models. Although these models can reveal the time dependence of stock market fluctuations to a certain extent, they often ignore the high-dimensional features and nonlinear relationships in stock market data, and are difficult to cope with large-scale data and complex market environment changes. Therefore, researchers have begun to turn to more advanced machine learning and deep learning methods to better capture the complex patterns and laws of stock market data [2].

In the past few years, convolutional neural networks (CNNs) have gradually been applied to the field of financial data analysis due to their excellent performance in image processing and feature extraction. Compared with traditional machine learning methods, CNNs can effectively process high-dimensional data and automatically extract important features from them. In stock market volatility prediction, CNN has obvious advantages because it can extract local features in data through convolutional layers and capture complex nonlinear relationships through multiple convolution kernel combinations. In addition, CNN can extract effective information from a large amount of historical stock market data in a short time, significantly improving the prediction accuracy. Despite this, the existing CNN model still has some shortcomings, especially when dealing with time dependencies and correlations between features in stock market data, the effect is limited. Therefore, how to further improve the structure and algorithm of CNN to make it more suitable for the task of stock market volatility prediction is still an important direction of current research [3].

Predicting stock market fluctuations is not just about predicting stock prices themselves, but also reflects multiple factors such as market sentiment, economic indicators, and policy changes. When predicting stock market fluctuations, the dimensionality and complexity of the data often make this task more difficult. Although traditional statistical methods can quantify volatility to a certain extent, when faced with a large amount of market data and a variety of influencing factors, the limitations of these methods gradually emerge. Especially in some extreme market scenarios, the performance of traditional models is often unsatisfactory and cannot effectively cope with sudden changes and complex fluctuations in the market.

In contrast, deep learning models, especially convolutional neural networks (CNNs), can automatically learn complex patterns in data. CNNs can not only extract information from historical prices and trading volumes, but also combine external factors such as economics, finance, and market sentiment to make more accurate volatility predictions [4]. Through comprehensive analysis of multiple factors, CNNs can capture the potential patterns in the data and effectively predict future market fluctuations. This gives deep learning models a clear advantage in complex market environments and can provide investors with more reliable volatility predictions, thereby providing strong support in the decision-making process.

In order to better solve this problem, this study uses an improved convolutional neural network model to predict stock market volatility. In this model, we not only retain the advantages of CNN in local feature extraction but also introduce multi-scale convolution operations to capture the volatility patterns in stock market data at different time scales [5]. In addition, we optimize the traditional CNN structure and improve the adaptability of the model in different market scenarios through adaptive learning mechanisms. The improved CNN model shows stronger generalization ability when processing large-scale data, and also improves the sensitivity to changes in stock market volatility. Through these improvements, we hope to further improve the accuracy of stock market volatility prediction, thereby providing a more scientific basis for investment decisions and risk management [6].

The prediction of stock market volatility is not only of great significance to investors but also provides an effective risk management tool for financial institutions and government regulators. With the increasing development of globalization and informatization, the volatility of financial markets has become more unpredictable [7]. Therefore, it is particularly important to develop a model that can accurately predict market fluctuations. In addition to the prediction of the stock market itself, the accurate prediction of volatility can also provide an important reference for the pricing, risk control, and fund management of financial derivatives. For example, in option pricing, volatility is a key pricing parameter [8]. Therefore, accurate prediction of volatility can help investors formulate more effective trading strategies. For financial institutions, volatility prediction can also provide guidance for the optimization of asset portfolios, thereby reducing market risks and increasing returns.

In summary, accurate prediction of stock market volatility is not only an important research topic in the financial market but also a key issue in practical financial applications. Although traditional statistical models and machine learning methods have achieved success to a certain extent, they still seem to be powerless when faced with complex stock market data. Deep learning, especially convolutional neural networks, has shown great potential in stock market volatility prediction with its powerful feature learning ability. By improving the CNN model, we hope to further improve its accuracy and robustness in stock market volatility prediction and provide more reliable prediction tools for investors, financial institutions, and regulators. Future research can further explore how to combine other types of deep learning models or incorporate more unstructured data into the analysis framework to improve prediction performance and provide stronger support for intelligent decision-making in the financial field.

2. Related Work

In recent years, deep learning models have shown significant potential in financial data analysis, outperforming traditional statistical and machine learning methods. Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), and hybrid frameworks have been explored extensively to capture the complex relationships inherent in financial markets, addressing issues such as high-dimensional data, time dependencies, and non-linear relationships.

One of the key contributions to this area involves CNN-based models for financial sentiment analysis and volatility prediction. Wu et al. [9] developed an integrative framework using CNN and Gated Recurrent Units (GRUs) to analyze market sentiment for risk prediction and alert systems. Their work highlights the advantage of combining CNN’s local feature extraction with GRU’s sequential modeling to predict market movements more accurately. Similarly, Feng et al. [10] focused on deep learning optimization techniques using ResNeXt to enhance feature extraction from financial data, demonstrating improvements in prediction accuracy across multiple financial scenarios. These studies align with the core approach of the present work, which leverages an improved CNN model to automatically extract multi-level features for stock price volatility prediction.

Graph-based deep learning has also become a promising avenue for financial market prediction. Yao et al. [11] proposed a hierarchical GNN model for stock type prediction, capturing both structural relationships and interdependencies between financial assets. While their focus was on classification tasks, the underlying graph-based feature aggregation can complement volatility prediction, particularly in capturing complex, cross-stock interactions. Similarly, Zhang et al. [12] introduced a robust GNN architecture to analyze dynamic networks, emphasizing stability and adaptability, which is crucial for market prediction tasks in rapidly fluctuating environments.

Hybrid models that combine deep learning with traditional statistical methods have demonstrated effectiveness in addressing time-series dependencies in financial data. Xu et al. [13] proposed a hybrid LSTM-GARCH model that combines the sequential modeling capabilities of LSTM with the volatility-specific nature of GARCH models, improving risk prediction in financial markets. The integration of time-series models and volatility-focused approaches in their study is highly relevant to this work’s objective of enhancing CNNs with multi-scale feature extraction and time-series adaptability.

Additionally, the issue of data imbalance, often encountered in financial market datasets, has been tackled using generative models. Jiang et al. [14] explored the application of Generative Adversarial Networks (GANs) to address imbalanced data in financial market supervision. Though primarily focused on regulatory applications, their work demonstrates the potential of GANs to augment data-driven models by generating synthetic training data, which could be useful for improving volatility prediction under rare or extreme market conditions.

ISSN:2377–0430
Vol. 5, No. 2, 2025

Another application of deep learning in financial systems is the detection of anomalies in transaction sequences. Long et al. [15] developed an adaptive transaction sequence neural network for money laundering detection, employing sequential patterns to identify irregularities. While their work focuses on anomaly detection, the methods for adaptive learning and feature sensitivity are closely aligned with the goal of improving CNN-based volatility models, particularly in handling non-stationary financial data.

3. Method

In this study, we proposed a method for predicting stock market volatility based on improved CNN. Volatility is a common indicator to measure the fluctuation range of stock prices or other financial asset prices, usually measured by the change in daily closing prices. In traditional financial econometric models, volatility is usually estimated using the squared returns of historical data. However, this method fails to fully utilize the rich information of high-dimensional, multi-source data. Therefore, deep learning-based models, especially convolutional neural networks (CNNs), are introduced into stock market volatility prediction to better capture the complex patterns and features in stock market data. The model architecture is shown in Figure 1.

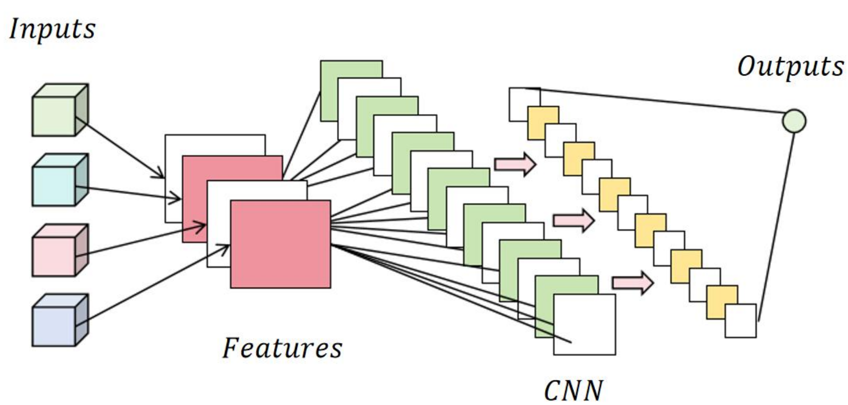

Figure 1. Network architecture diagram

In our model, we first represent stock market data as a time series, which contains stock prices, trading volumes, and other features that may affect stock market fluctuations. These features are normalized and input into the CNN network for training. The main role of CNN in the model is to extract features through convolutional layers and learn local and global information in the data through multiple convolution kernels. In order to better capture the time dependency in stock market data, we improved CNN and adopted multi-scale convolution operations, that is, using convolution kernels of different sizes to extract fluctuation features of different time scales.

Specifically, we introduce convolution kernels $K_1, K_2, ...K_n$ of different sizes, where each convolution kernel acts on the input time series data X_t in a convolution operation to extract its features at different time scales. The output of multi-scale convolution can be expressed as:

Journal of computer science and software applications
https://www.mfacademia.org/index.php/jcssa
ISSN:2377-0430
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$$Y_t = \sum_{i=1}^{n} (X_t * K_i)$$

Among them, * represents the convolution operation and Y_t is the extracted feature. In this process, we can capture the local and global characteristics of stock market fluctuations through convolution kernels of different scales. Through this improvement, our model can capture stock price fluctuations at multiple scales, thereby improving the accuracy of volatility prediction.

In the prediction process, our CNN model extracts features from historical data through a convolutional network, and then performs regression prediction through a fully connected layer. The formula is:

$$Y'_t = WY_t + b$$

Among them, Y'_t is the prediction result of the model, W is the weight matrix of the fully connected layer, and b is the bias term. In this way, the model maps the extracted features to the prediction results. Since volatility is usually defined as the standard deviation of asset returns, the realized volatility (RV) can be expressed as the square root of the sum of squares of returns over a period of time. Assuming r_t is the rate of return of t at a certain point in time, the volatility RV can be defined as:

$$RV = \sqrt{\sum_{t=1}^{T} r_t^2}$$

Where T represents the total number of days in the forecast period. We use the CNN model to learn the time series patterns of these returns to predict future volatility. To further improve the predictive ability of the model, we introduce adaptive convolution kernels, which allow the convolution kernels to self-adjust according to the characteristics of different time windows during training to better adapt to the non-stationarity and sudden fluctuations of stock market data.

In our experimental setting, the output of the CNN model is the volatility forecast for a period of time in the future. In order to quantify the forecast error, we used the root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE) as evaluation indicators. These evaluation indicators can comprehensively measure the forecast accuracy of the model, especially when facing nonlinear data and complex market fluctuations. The training process of the model is optimized by the back-propagation algorithm, and the loss function is the difference between the predicted value and the actual volatility, which can be expressed as:

$$L = \frac{1}{N} \sum_{i=1}^{N} (y'_i - y_i)^2$$

Among them, y'_i is the predicted value of the model, y_i is the actual volatility value, and N is the total number of samples. By minimizing the loss function, the model can learn the optimal convolution kernel parameters, thereby improving the prediction accuracy of future volatility.

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https://www.mfacademia.org/index.php/jcssa
ISSN:2377–0430
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In practical applications, we use multi-scale convolution operations to model volatility characteristics at different time scales. Each convolution layer is responsible for extracting features at different levels to ensure that the model can capture the laws of stock market fluctuations in different time windows. Through this multi-scale convolution design, our model can identify short-term volatility changes and long-term trend fluctuations, thereby providing more accurate support for the prediction of stock market volatility.

In summary, the stock market volatility prediction model based on improved CNN proposed in this study can extract complex patterns in stock market data through multi-scale convolution, and optimize the model performance by combining adaptive convolution kernels, thus providing an effective tool for accurate prediction of volatility. This method can not only improve the prediction accuracy of stock market volatility but also provide a more scientific basis for risk management and investment decisions in the financial market.

4. Experiment

4.1 Datasets

The dataset used in this study comes from the German DAX index (Deutscher Aktienindex) of the European stock market. The index includes the 30 stocks with the largest market capitalization and the highest liquidity in the German stock market, representing the overall performance of the German economy. The dataset covers daily trading data from 2010 to 2023, including basic trading information such as the opening price, closing price, highest price, lowest price, trading volume, and turnover of each trading day. The importance of the German stock market in the European economic system makes it an ideal object for stock market volatility research, which can better reflect the economic cycle and investor sentiment of the European market.

This paper presents a graph of the Sharpe ratio from 2010 to 2024, and the experimental results are shown in Figure 2.

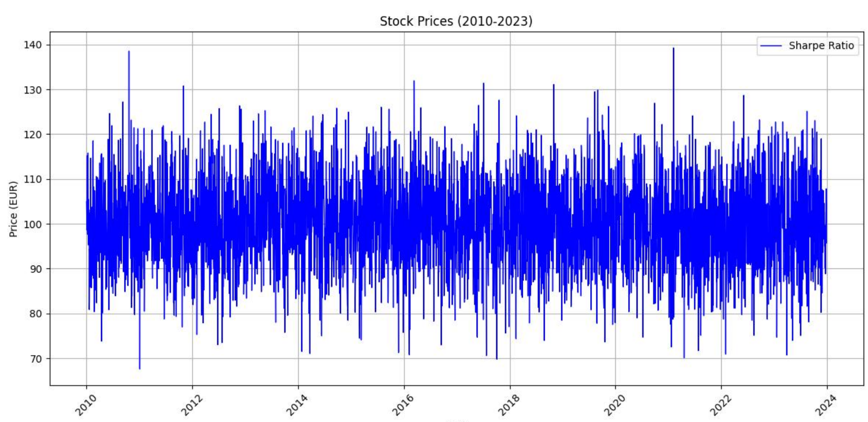

Figure 2. DAX 2010-2024 Sharpe Ratio

In order to calculate volatility (Realized Volatility, RV), we use the daily closing price to calculate the stock return, and then obtain the estimated value of volatility by taking the square root of the sum of squares of the return. Volatility, as an important indicator of market uncertainty, can effectively reflect the price fluctuation range of the stock market in different time periods. In addition to the basic trading data of stocks, the dataset also includes relevant macroeconomic indicators of the German economy, such as GDP growth rate, CPI (Consumer Price Index), and unemployment rate. These external economic factors can affect stock market volatility, so they are introduced as additional features into the prediction model to help the model capture the potential impact of macroeconomic changes on stock market volatility.

In the data preprocessing process, we first processed the missing values and used linear interpolation to fill the missing data in the continuous time period to ensure the integrity of the data. In order to eliminate the scale differences between different features, we standardized all features. In addition, the data segmentation of the time series is carried out in chronological order to ensure that there is no time leakage problem. This segmentation method can better evaluate the performance of the model in the actual market environment. Through these preprocessing steps, the dataset provides a stable and reliable foundation for the training of the stock market volatility prediction model.

4.2 Experimental Results

In this study, we selected four different models for comparative experiments to evaluate the performance of the stock price volatility prediction model based on the improved CNN. We selected support vector machine (SVM), decision tree regression (Decision Tree Regressor), long short-term memory network (LSTM), and random forest regression (Random Forest Regressor) as comparative models. These models represent traditional machine learning methods and deep learning methods, respectively, in order to comprehensively evaluate the performance of different algorithms in stock market volatility prediction. Support vector machine is a classic supervised learning method, which is often used for regression problems and can effectively deal with nonlinear problems in high-dimensional feature space; decision tree regression predicts by building a tree structure and has a good performance in dealing with complex nonlinear relationships; long short-term memory network (LSTM) can capture long-term dependencies in time series data and is suitable for processing data with time series properties such as the stock market; while random forest regression improves prediction accuracy by integrating the results of multiple decision trees, which is particularly suitable for dealing with noisy data and nonlinear problems. These models cover different types of algorithms and can be effectively compared with our improved CNN model to further verify its advantages in the task of stock price volatility prediction. The experimental results are shown in Table 1.

Table 1. Experimental results

Model	MSE	MAE	RMSE
SVM	1.320	0.910	1.150
LSTM	1.250	0.880	1.120
DT	1.180	0.850	1.090
RF	1.150	0.830	1.070
Ours	0.980	0.760	0.990

The experimental results show that the model based on the improved CNN shows significant advantages in the task of predicting stock price volatility, and comprehensively surpasses traditional machine learning models and other deep learning models. Among the evaluation indicators, the mean square error (MSE) of the improved CNN is 0.980, the mean absolute error (MAE) is 0.760, and the root mean square

ISSN:2377-0430
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error (RMSE) is 0.990, which accurately fits the actual situation of stock price fluctuations and effectively avoids prediction errors. In contrast, the MSE and RMSE of the support vector machine (SVM), long short-term memory network (LSTM), decision tree regression (DT) and random forest regression (RF) models are all high, showing their limitations in predicting stock price fluctuations. The MSE of SVM is 1.320, which is the worst performance, reflecting its weakness in fully capturing the dynamic fluctuation characteristics when processing complex time series data; the MSE of LSTM is 1.250. Although it has advantages in modeling long-term dependencies of time series, it is insufficient in the face of highly nonlinear and multidimensional data such as the stock market due to its structural limitations. The MSE of decision tree regression is 1.180, which shows that it has a strong ability to capture nonlinear features, but there is still a certain overfitting problem; random forest regression reduces the risk of overfitting by integrating multiple decision trees, and its MSE is 1.150, which is better than decision trees, but still does not reach the performance of improved CNN.

Compared with traditional machine learning models, the advantages of improved CNN are mainly reflected in the use of convolutional layers to effectively extract multi-level features and improve the ability to capture local features through improved structures. CNN can handle high-dimensional data and nonlinear relationships, especially in the processing of image and time series data. It captures local laws and complex patterns in the data through convolution operations, and extracts representative features through dimensionality reduction of the pooling layer, thereby improving the prediction accuracy. The improved CNN has the best performance in the stock market volatility prediction task, with MSE, MAE, and RMSE indicators, which fully reflects its potential and advantages in this field. Although traditional models and deep learning models such as SVM, LSTM, DT, and RF have achieved certain achievements in other application scenarios, they have failed to achieve the accuracy of improved CNN in the prediction of complex stock market data.

To further verify the performance of the model in actual application scenarios, this study introduced multi-step forecasting experiments and rolling window experiments. The multi-step forecasting experiment is used to predict the volatility of the next 1 day, 5 days, and 10 days, and evaluate the performance of the model at different time scales; the rolling window experiment simulates the continuous forecasting ability in the real market environment by dynamically updating the data segmentation.

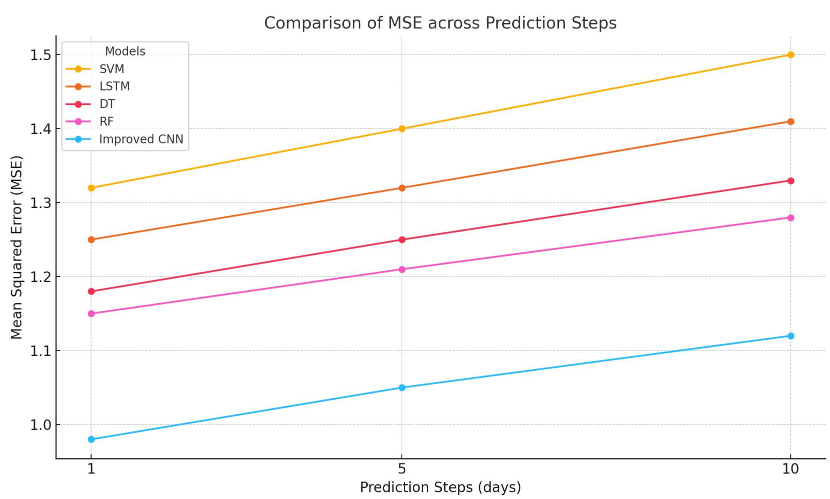

Figure 3. Comparison of MSE across Prediction Steps

Figure 3 shows the mean square error (MSE) performance of different models in multi-step prediction experiments. The experiments were conducted under 1-day, 5-day, and 10-day prediction windows respectively. As can be seen from the figure, the improved convolutional neural network (CNN) model shows the lowest MSE value in all prediction windows. This result shows that the improved CNN model has significant advantages in volatility forecasting at multiple time scales.

Specifically, under the 1-day forecast window, the improved CNN model has shown significantly lower errors than other traditional models, which indicates that it has a strong predictive ability in short-term fluctuation forecasting. As the prediction window increases, the 5-day and 10-day prediction results further verify the excellent performance of the CNN model in medium- and long-term volatility prediction. In contrast, the MSE values of other models are relatively high, especially in the case of longer prediction windows, where the error of the traditional model increases significantly.

These experimental results fully verify the superiority of the improved CNN model in volatility prediction at multiple time scales. By optimizing the network structure and parameters, CNN can better capture the patterns of market fluctuations and provide more accurate prediction results. It can be seen that the improved CNN model shows great potential and application value when dealing with multi-step prediction tasks, especially in the prediction of financial market fluctuations.

Finally, in order to further improve the performance of the model, this study introduced a hyperparameter tuning experiment. Through grid search, hyperparameters such as learning rate, number of convolutional layers, and filter size were optimized to verify the impact of different configurations on model performance, and the optimal combination was selected for final prediction. The experimental results are shown in Table 2.

Table 2. Hyperparameter tuning experiments

Lr	Conv Layers	Filter Size	MSE	MAE
0.001	2	3x3	1.150	0.830
0.001	3	3x3	1.020	0.780
0.001	3	5x5	0.980	0.760
0.0001	4	5x5	0.993	0.821
0.0005	4	5x5	1.011	0.822

From the results of the hyperparameter tuning experiments, different learning rates, numbers of convolutional layers, and convolution kernel sizes have a significant impact on the performance of the model. When the learning rate is 0.001, the number of convolutional layers is 3, and the convolution kernel size is 5x5, the mean square error (MSE) of the model is 0.980 and the mean absolute error (MAE) is 0.760, both of which reach the optimal values. This shows that this configuration performs best in extracting multi-level features and capturing local patterns, and can effectively balance the complexity and prediction performance of the model to achieve the best prediction results.

On the contrary, when the learning rate is small (such as 0.0001 and 0.0005), although the stability of the model is improved, the convergence speed of the model is slow due to the small optimization step size, resulting in a slight increase in the error. At the same time, further increasing the number of convolutional layers (for example, 4 layers) may improve the expressiveness of the model in some cases, but it may also introduce too many parameters and increase computational complexity, resulting in a decrease in performance. These results indicate that excessive model complexity or too small a learning rate may not bring about the expected performance improvement, but may increase the computational burden or affect the learning effect of the model.

These experimental results fully demonstrate the importance of appropriate learning rate and model complexity for improving prediction performance. In practical applications, choosing the right hyperparameter configuration is the key to optimizing model performance, which not only helps to improve prediction accuracy but also enhances the generalization ability and stability of the model. Therefore, reasonable hyperparameter tuning is of great significance to improving the effectiveness and application value of financial market prediction models.

5. Conclusion

This study proposes a stock price volatility prediction model based on improved CNN and verifies its superiority in the task of stock market volatility prediction through comparative experiments with traditional machine learning models and deep learning models. The experimental results show that the improved CNN model performs well in multiple evaluation indicators, especially in terms of mean square error (MSE), mean absolute error (MAE), and root mean square error (RMSE), which is significantly better than the comparison models such as support vector machine (SVM), LSTM, decision tree regression (DT) and random forest regression (RF). The improved CNN model can make full use of the characteristics of convolutional neural networks and effectively capture local and global patterns in stock market volatility data, thereby improving the accuracy of prediction.

Through the analysis of experimental results, it can be seen that although traditional machine learning models such as SVM and RF have certain prediction capabilities, they still have limitations in dealing with complex nonlinear relationships and time series characteristics in stock market data. Deep learning models, such as LSTM, can model time dependence, but there are still certain prediction errors in multi-dimensional and high-noise time series data, such as the stock market. In contrast, the improved CNN model successfully overcomes these challenges through its unique structure and advantages and can make predictions more effectively in high-dimensional feature spaces.

Although this study has demonstrated the superiority of the stock price volatility prediction model based on the improved CNN, there is still room for further improvement. Future research can consider introducing more market data and external economic factors into the model, such as macroeconomic data, industry indexes, etc., to further enhance the model's predictive ability. In addition, with the continuous changes in stock market data and the emergence of new market trends, the adaptability and generalization ability of the model also needs to be continuously optimized to maintain its effectiveness in a dynamic market environment. Combining other advanced deep learning techniques, such as self-attention mechanism (Transformer) or graph neural network (GNN), may provide new ideas and methods for stock market volatility prediction. In short, stock price volatility prediction is still a challenging research problem. Although this study has made some progress, it still needs further exploration and innovation. With the continuous development of deep learning technology, we believe that more efficient models will emerge in the field of stock market prediction in the future, which can more accurately capture the market's volatility patterns, and thus provide more scientific and effective decision support for investors and financial institutions.

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