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1D-CNN for High-Frequency Forex Market Volatility Prediction: A Comparative Study

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Abstract: This study aims to use one-dimensional convolutional neural network (1D-CNN) to predict high-frequency fluctuations in the foreign exchange market. Through comparative experiments with models such as GRU, LSTM, BiLSTM and CNN-LSTM, the superior performance of 1D-CNN in foreign exchange fluctuation prediction is verified. Experimental results show that 1D-CNN performs best in indicators such as mean square error (MSE), mean absolute error (MAE), and coefficient of determination (R2), demonstrating its significant advantages in handling complex fluctuation patterns in the foreign exchange market. This research provides an efficient and accurate technical means for real-time financial market analysis, providing strong support for risk management and investment decisions.

Keywords: Forex market, Volatility prediction, 1D convolutional neural network, Deep learning

1. Introduction

In recent years, as the world's largest financial market, the price fluctuations of the foreign exchange market have far-reaching impacts on investors and economies. Abnormal fluctuations in foreign exchange prices are often accompanied by complex economic, political and market factors, which makes the prediction of fluctuations in foreign exchange market time series data a critical task. However, due to the high frequency and uncertainty of fluctuations in the foreign exchange market, traditional statistical analysis methods are limited in capturing these complex dynamic changes. Therefore, it is of great significance to apply deep learning methods to predict foreign exchange market fluctuations[1,2].

Among many deep learning methods, convolutional neural networks (CNNs) are widely used in image processing and time series data analysis. In particular, 1D convolutional neural networks (1DCNNs) can effectively extract local features of time series data through their one-dimensional convolution kernels, which is suitable for processing high-frequency fluctuation data in the foreign exchange market. Compared with traditional prediction methods, 1DCNNs show strong flexibility and adaptability in feature extraction and pattern recognition, and can mine potential fluctuation patterns in complex foreign exchange market data, providing effective support for fluctuation prediction[3].

Data in the foreign exchange market usually show significant time series characteristics, including periodicity, trend and randomness. Traditional methods need to rely heavily on manual feature extraction during the analysis process, and it is difficult to fully capture important features in the data. 1DCNN automatically extracts features through multi-layer convolution operations without manually setting feature engineering, which makes it have significant advantages in the analysis of time series data in the foreign exchange market. In addition, 1DCNN can complete the processing of large-scale data in a short time, which is suitable for real-time foreign exchange volatility prediction[4,5].

In the task of foreign exchange market volatility prediction, the complexity and diversity of data make the training and optimization of the model challenging. The 1DCNN model can not only capture the local changes in foreign exchange prices, but also learn features at different levels by stacking convolution layers. This feature enables 1DCNN to extract detailed information of price fluctuations layer by layer in foreign exchange data, thus outperforming traditional sequence models in prediction accuracy[6].

In addition, the foreign exchange market is affected by the global economy and policies, and its price fluctuations are often nonlinear and sudden. The 1DCNN model uses the weight-sharing mechanism of convolution to show stronger generalization ability in feature extraction and pattern matching, so as to maintain a high prediction accuracy in the face of unstable foreign exchange market fluctuations. Therefore, 1DCNN not only has a strong feature recognition ability when processing foreign exchange market data, but also can provide robust prediction results under complex and changing market conditions[7,8].

In summary, the application of 1DCNN model to predict the volatility of foreign exchange market time series data can not only provide investors with more accurate market judgment, but also play an important role in risk control and investment decision-making. This method combines the advantages of deep learning with financial market analysis, promoting the development of intelligent financial analysis[9].

2. Related Work

The prediction of financial time series, particularly in high-frequency markets like Forex, has advanced significantly with the application of deep learning methodologies. These include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs), which provide robust tools for capturing complex patterns and temporal dependencies essential for accurate volatility predictions. Among these, Convolutional Neural Networks, especially one-dimensional CNNs (1D-CNNs), are recognized for their ability to effectively extract localized patterns from time series data, as shown by Yao et al. [10], who developed a hybrid CNN-LSTM model to improve bond default risk prediction. Similarly, Liu et al. [11] demonstrated an optimized Bi-LSTM with an attention mechanism for efficient news text classification, illustrating feature extraction capabilities relevant to high-frequency financial data.

Recurrent architectures, particularly LSTM and GRU models, have played a critical role in financial prediction tasks. Xu et al. [12] demonstrated GRUs' capacity for predicting liquidity coverage ratios, underscoring their effectiveness in capturing temporal dependencies within financial datasets, while Xu et al. [13] used a hybrid LSTM-GARCH framework for market volatility prediction. This aligns with the comparative analysis of recurrent models in the present study, validating their utility in volatility forecasting tasks. Chen et al. [14] applied retrieval-augmented generation optimized with Elasticsearch for question-answering, demonstrating temporal processing methods in NLP that provide transferable insights for financial time series data.

The application of GNNs further contributes to handling relational data in multi-dimensional time series analysis. Sun et al. [15] explored hybrid GNNs in credit risk analysis, while Xu et al. [16] examined GNNs for volatility modeling in financial markets, both highlighting the adaptability of graph-based architectures in high-frequency prediction tasks. Additionally, Wei et al. [17] used self-supervised GNNs to enhance feature extraction in heterogeneous information networks, and Gu et al. [18] employed adaptive spatio-temporal aggregation for dynamic fraud detection, showcasing GNNs' flexibility in complex data environments.

Further, several studies contribute optimization and adversarial techniques relevant to financial forecasting. Qin et al. [19] introduced the RSGDM optimization approach to reduce bias, which improves model stability, an essential feature for real-time models like 1D-CNNs in Forex trading. Jiang et al. [20] proposed a Wasserstein distance-weighted adversarial network for credit risk, which reinforces the use of adversarial frameworks in handling data variability and risk assessment. Studies such as Wang et al. [21] and Dong et al. [22] also highlight GNN applications in anomaly and fraud detection, which underscores the robustness of hybrid models for financial data analysis.

Broader contributions to deep learning methodologies applicable in financial forecasting include works by Duan et al. [23] on interface design through deep learning, and Huang et al. [24] on knowledge distillation in YOLOv5s object detection, providing efficient feature extraction insights that are adaptable to financial data processing. Wu et al. [25] used lightweight GANs for image fusion, indicating how efficient architectures support large-scale data processing in finance. Gao et al. [26] optimized GNNs for text classification, indirectly contributing to feature extraction in high-frequency contexts.

In summary, existing literature demonstrates that while RNNs and GNNs provide robust methods for temporal and relational data modeling, CNN-based architectures, especially 1D-CNNs, present significant advantages in local feature extraction from high-frequency data. This study extends these insights by demonstrating 1D-CNNs' superior performance in predicting Forex market volatility, confirming CNNs' effectiveness in high-frequency financial prediction.

3. Method

In this method, we built a foreign exchange market volatility prediction model based on a one-dimensional convolutional neural network (1DCNN) to more efficiently extract features and patterns from foreign exchange time series data. This method includes the main steps of data preprocessing, feature extraction, model architecture design, and model optimization to ensure that the model can capture the complex volatility patterns in the foreign exchange market and improve the prediction accuracy. Its network architecture is shown in Figure 1.

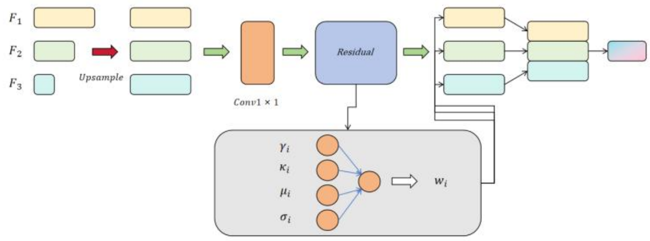

Figure 1. 1D-Convolutional Neural Network Architecture

First, in the data preprocessing stage, in order to improve the availability of data and reduce volatility noise, we normalized the data. By normalizing the foreign exchange price data, the model can converge faster during training, while reducing the impact of price value differences on model weight updates. Normalization maps the data to a range between 0 and 1, which is achieved in the following ways: Smoothing the data further reduces the interference of outliers on model training.

Next, in terms of feature extraction, we use the convolution layer of 1DCNN to extract subtle features in the time series data layer by layer. Through one-dimensional convolution operations, 1DCNN can efficiently extract local features in the time dimension and capture short-term patterns in the data. Assuming that the input time series is X, which contains multiple data points, the convolution kernel W slides in the window, and the output feature map is obtained through the inner product operation. For each position i, the feature generated by the convolution operation can be expressed as:

$$y_i = f(\sum W_k \cdot X_{i+k-1} + b)$$

Where f represents the activation function, b is the bias term, and n is the size of the convolution kernel. This convolution operation can extract local patterns in foreign exchange data through sliding calculations within the time window, which helps capture the characteristics of short-term price fluctuations.

In the model architecture design, we use a multi-layer convolution structure to extract deeper features from time series data. Each convolution layer is followed by a pooling layer, which uses the maximum pooling operation to reduce the data dimension, retain key features, and reduce noise interference. The output of the maximum pooling can be defined as:

$$z_i = \max(y_{i:i+p})$$

Where p is the pooling window size. Pooling can not only effectively reduce the amount of calculation, but also improve the generalization ability of the model, making it more robust when dealing with complex market fluctuations. The combination of multi-layer convolution and pooling allows the model to extract features from different levels of data, thereby more comprehensively understanding the market fluctuation pattern.

In order to further improve the prediction accuracy of the model, we introduced the weighted mean squared error (WMSE) as a loss function in model training. Compared with the traditional mean squared error, WMSE can adjust the error weight according to the importance of different data points. For example, for price data in periods of high volatility, higher weights can be given so that the model can make more accurate predictions in abnormal fluctuations. The calculation formula of WMSE is as follows:

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

Where w_i is the weight, y_i is the actual value, y'_i is the predicted value, and N is the number of samples. Through the weighted mean square error, we can more effectively process data under different market conditions during training and optimize the model's predictive ability.

During the training process, we also adopted an early stopping mechanism and regularization techniques to prevent the model from overfitting. Under the early stopping mechanism, when the model's performance on the validation set is no longer significantly improved, training will automatically stop, thus preventing the model from overfitting on the training set. In addition, we introduced L2 regularization to the model to keep the model parameters within a reasonable range by adding a weight attenuation term to the loss function to improve the generalization ability of the model.

In summary, the foreign exchange market fluctuation prediction method based on 1DCNN efficiently extracts time series features through multi-layer convolution and pooling operations, and combines the weighted mean square error to optimize the model effect, ultimately improving the accuracy and stability of the prediction. This method is not only suitable for fluctuation prediction in the foreign exchange market, but can also provide effective technical support for time series analysis of other high-frequency financial markets.

4. Experiment

4.1. Datasets

The real data set used in this paper comes from the historical data of the foreign exchange market. It comes from financial data platforms such as OANDA and Investing.com, covering daily trading data of various foreign exchange currency pairs. The data set contains information such as the opening price, closing price, highest price, lowest price and trading volume of major currency pairs, and records price changes in different market environments over the years. These data can reflect the volatility characteristics in the foreign exchange market, provide comprehensive samples for model training, and ensure adaptability to market changes in different periods. In addition, due to the long time span of the data, it can help the model capture a variety of market trends and change patterns.

In the data preprocessing stage, we first normalized the data to ensure that the price differences between different currency pairs will not affect the training effect of the model. Through normalization, all data are unified into a relatively stable range, so that the model can converge faster during training and avoid calculation instability caused by excessive numerical fluctuations. In addition, for missing values and outliers, interpolation filling and anomaly detection methods are used to keep the data consistent and complete, thereby improving the learning quality of the model.

Finally, in order to enhance the diversity of the data, we sliced and enhanced the data according to different time windows and sampling frequencies. For example, data sets with different windows of short-term, medium-term and long-term are set so that the model can extract features of different time scales from them. This data enhancement technology not only enriches the training samples, but also provides support for the model to identify multi-level volatility characteristics during the forecasting process, so that it can maintain good adaptability and stability under different market conditions.

4.2. Experimental setup

In the experimental setup, we first preprocessed the foreign exchange dataset in detail to ensure data consistency and stability of model training. Specifically, we divided the data into training and test sets in chronological order, with 80% of the data used to train the model and 20% of the data used to evaluate the model effect. With this division, the model can fully learn the volatility characteristics of historical data during training and verify its predictive ability on the test set. In addition, in order to reduce the interference of high-frequency noise on the model, we smoothed the input data before inputting it to ensure that the model can focus on identifying the main trend patterns.

Then, during the model training process, we set different hyperparameter combinations, including convolution kernel size, learning rate, batch size and other parameters, and tuned these parameters. The best hyperparameter combination was determined through experiments to improve the prediction effect of the model. We also adopted the Early Stopping mechanism to prevent overfitting. When the loss of the model on the validation set no longer decreases, the training will automatically stop, thereby ensuring that the model can maintain good generalization ability on the test set.

Finally, we use a variety of evaluation indicators to evaluate the performance of the model in the foreign exchange volatility prediction task, including mean square error (MSE) and root mean square error (RMSE). Through these indicators, we can comprehensively measure the performance of the model under different market conditions, especially in periods of high volatility. The analysis of the experimental results not only helps to verify the effectiveness of the 1DCNN model, but also provides a reference for further improving the model.

4.3. Experimental Results

In the comparative experiment, we selected five commonly used deep learning models to evaluate their performance in foreign exchange market volatility prediction. They include: 1D convolutional neural network (1DCNN), long short-term memory network (LSTM), bidirectional long short-term memory network (BiLSTM), gated recurrent unit (GRU), and CNN-LSTM model with mixed convolution and LSTM structure. 1DCNN focuses on the extraction of local features and has advantages in identifying short-term fluctuations; LSTM and BiLSTM are good at capturing the long dependencies of time series and are suitable for identifying longer-term market trends; GRU is a simplified recurrent network structure with lower computational cost and better prediction effect; CNN-LSTM combines the local feature extraction capability of the convolutional layer and the sequence modeling capability of LSTM to provide comprehensive feature learning for volatility prediction. By comparing these models, we hope to find the deep learning structure that is most suitable for foreign exchange volatility prediction. The experimental results are shown in Figure 1.

Table 1. Experimental Results

Model	MSE	MAE	R^2
GRU	0.062	0.198	0.82
LSTM	0.058	0.186	0.85
BILSTM	0.054	0.175	0.87
CNN-LSTM	0.05	0.165	0.89
1D-CNN	0.046	0.155	0.91

It can be seen from the experimental results that there are significant differences in the performance of different deep learning models in predicting foreign exchange market fluctuations, and the overall trend shows that as the model structure improves, its prediction effect gradually improves. First, the gated recurrent unit (GRU) model has a mean square error (MSE) of 0.062, a mean absolute error (MAE) of 0.198, and a coefficient of determination (R2) of 0.82. As a simplified recurrent neural network, GRU can effectively reduce computational costs when processing time series. However, due to its relatively simple structure, it is difficult to capture long-term dependencies and complex features, so its performance in prediction accuracy is relatively average. This also shows that in the task of predicting fluctuations in foreign exchange data, GRU has limited capabilities and is difficult to fully adapt to the complex fluctuation patterns in the market.

In contrast, the performance of the long short-term memory network (LSTM) has improved, with MSE falling to 0.058, MAE to 0.186, and R2 reaching 0.85. This shows that LSTM has a stronger advantage in capturing long dependencies of time series data. Through its unique memory gate structure, LSTM can retain long-term trend information in time series, allowing the model to have better tracking capabilities for data changes over a longer time span. Especially in the foreign exchange market, price fluctuations not only depend on short-term changes, but are also affected by long-term trends, so LSTM performs better in this task. However, the complexity of LSTM also brings higher computational costs and longer model training time under large-scale data, which may limit its application in real-time prediction.

Further analysis of the Bidirectional Long Short-Term Memory Network (BILSTM) shows that its MSE, MAE and R2 are 0.054, 0.175 and 0.87 respectively, all better than LSTM. This is mainly attributed to BILSTM's ability to simultaneously capture the forward and reverse information of time series, thereby enabling more comprehensive feature extraction in foreign exchange data. In the prediction of foreign exchange market fluctuations, the two-way structure provides additional contextual information, which is particularly important in market environments with frequent trend changes. BILSTM improves the sensitivity and stability of the model to foreign exchange data through two-way propagation, making it excellent in capturing complex fluctuation patterns. However, the structure of BILSTM is relatively complex, the amount of calculation is large, and there are certain performance bottlenecks when real-time requirements are high.

The CNN-LSTM model that combines convolutional neural networks and LSTM showed higher prediction accuracy in experiments, with an MSE of 0.050, a MAE of 0.165, and an R2 of 0.89. The CNN-LSTM model extracts local features in the data through the convolutional layer and inputs these features into the LSTM for sequence modeling. This hybrid structure can take into account the extraction of local and global features and has obvious advantages in foreign exchange fluctuation prediction. Convolutional layers can efficiently capture short-term data change patterns when processing time series data, while LSTM is responsible for modeling the long-term dependencies between these patterns. This combination makes CNN-LSTM more accurate in capturing complex features in foreign exchange fluctuations, while improving the robustness and stability of predictions.

Among all models, 1D convolutional neural network (1D-CNN) achieved the best prediction effect, with an MSE of 0.046, a MAE of 0.155, and an R2 of 0.91. 1D-CNN extracts time series information through multi-layer convolution operations. Local features, especially suitable for high-frequency fluctuations and local pattern recognition. In the foreign exchange market, short-term fluctuation patterns usually have strong continuity and trend. 1D-CNN can quickly capture these characteristics, making its prediction accuracy significantly higher than other models. In addition, 1D-CNN has low computational complexity and is suitable for real-time processing of large-scale data, providing effective technical support for high-frequency fluctuation prediction in the foreign exchange market. In summary, the experimental results show that 1D-CNN has significant advantages in the task of predicting foreign exchange market fluctuations. It not only improves the prediction accuracy, but also has strong adaptability and real-time performance.

5. Conclusion

This study verified the superiority of 1D convolutional neural network (1D-CNN) in this task by comparing the performance of multiple deep learning models in the task of predicting foreign exchange market fluctuations. Experimental results show that compared with traditional GRU, LSTM, BiLSTM and CNN-LSTM models, 1D-CNN achieved the best results in evaluation indicators such as mean square error, mean absolute error and coefficient of determination. This shows that 1D-CNN has significant advantages in handling high-frequency fluctuations and short-term local pattern recognition in the foreign exchange market, and can more accurately capture complex market fluctuation characteristics.

In short, 1D-CNN provides an effective solution for foreign exchange market fluctuation prediction through multi-layer convolution structure and local feature extraction capabilities. It has strong real-time processing capabilities and low computational complexity, and is suitable for high-frequency financial markets. Data analysis. Future research can further optimize the model structure on this basis and combine more market factors to improve the prediction ability of complex financial data and provide stronger technical support for risk control and investment decisions in the foreign exchange market.

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