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Application of deep learning algorithms in predicting the exchange rate of Chinese yuan against the US dollar

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Abstract. This paper mainly studies the feasibility of using deep learning algorithms to predict the exchange rate between the Chinese yuan and the US dollar. Firstly, this study chooses the Long Short Term Memory Network (LSTM) as the main algorithm, which is a deep learning model suitable for processing time series data. Then, the study collects a large amount of data, including historical exchange rate data, macroeconomic indicators, and political events that may affect exchange rates. These data provide sufficient information for the model to learn and predict exchange rate fluctuations. The study found that the deep learning model can accurately predict the volatility of the RMB US dollar exchange rate by contrasting the calculated results of the pattern with effective exchange rate record, and its predicted results have high stability. Deep learning has great potential in the field of exchange rate forecasting, providing more accurate predictive information for financial transactions.

Keywords: Deep learning, Exchange rate, Chinese Yuan, US Dollar.

1. Background and Purpose

Exchange rate forecasting plays an important role in international trade, investment and financial markets [1]. Accurate exchange rate forecasting is essential for business decision-making, risk management and investment strategy development. For import and export companies, accurately predicting exchange rates can help them develop reasonable pricing and purchasing strategies, thereby improving competitiveness and profitability. For investors, accurately predicting exchange rates can help them decide when to buy or sell forex to maximize profits or reduce risk. However, exchange rate forecasting faces some challenges. First of all, the exchange rate is affected by various factors, including economic indicators, political events, market psychology, etc., which makes forecasting complex and difficult. Second, exchange rate data is highly time-series dependent and nonlinear, and traditional statistical models struggle to capture these complexities. In addition, the high volatility and uncertainty of the foreign exchange market also increases the difficulty of forecasting. Therefore, in order to effectively address these challenges, emerging technologies and methods, such as deep learning algorithms, need to improve the accuracy and stability of exchange rate forecasts.

1.1. Research Needs

In financial markets, exchange rate forecasting has always been the focus of investors and traders. However, traditional economic models often fail to fully take into account the complex nonlinear characteristics and time series dependencies of exchange rate fluctuations, resulting in low forecast accuracy. With the development of deep learning technology, more and more scholars have begun to explore the feasibility of using deep learning algorithms for exchange rate forecasting [2]. Compared with traditional models, deep learning-based exchange rate forecasting models can better capture the and time-series characteristics of exchange rate fluctuations and improve the prediction accuracy to a certain extent. Therefore, the study of exchange rate prediction model based on deep learning has become one of the hot spots in the current financial research field. This paper aims to explore the use of long-term short-term memory network to predict the exchange rate of Chinese RMB against the US dollar to improve the correctness and steadiness of exchange rate forecasting.

1.2. Research Objectives

The research objective of this article is to make exact forecast of the exchange rate of Chinese RMB against the US dollar based on deep learning algorithms, especially long short-term memory networks (LSTMs). Exchange rate fluctuations have a significant impact on businesses and investors, so providing reliable exchange rate forecast information is essential to make strategic decisions, price products appropriately, and manage cross-border investment risks. In the current complex and changeable financial market environment, traditional statistical models are often difficult to capture the nonlinear and temporal dependencies in exchange rate data, while deep learning algorithms have stronger flexibility and predictive capabilities. Therefore, this study aims to construct a stable and highly accurate exchange rate forecasting model, and to obtain reliable prediction results for future exchange rate changes by effectively using factors such as historical exchange rate data and corresponding economic indicators. This will provide important decision-making support to financial market participants, reducing the risk of decision-making and improving investment returns. In addition, the results of this research will also promote the application research of deep learning in the financial field, provide reference and enlightenment for relevant academic circles, and facilitate the further development of deep learning in the fields of financial forecasting and time series analysis. In general, the research objectives and significance of this paper are not only reflected in economic practice, but also have a positive impact on the application of deep learning in academia.

2. Data Collection and Preprocessing

The data sources of this study are mainly the RMB against the US dollar exchange rate data and corresponding economic indicator data released by the China Foreign Exchange Trading Center, including GDP, trade data, CPI, etc. This study selects all data from January 2010 to December 2022 as a sample. In terms of data preprocessing, the study first carried out data cleaning and outlier removal to ensure the accuracy and reliability of the data. Next, the study differentially processes the raw data and transforms it into a stationary sequence to eliminate non-stationarity. In addition, the study performs feature engineering, selected some representative and influential economic indicators, and normalized them to the range of [0,1] as input variables to the model [3]. Through the above preprocessing and feature engineering, the study obtains a set of high-quality exchange rate time series data that meets the modeling requirements, which settles a firm data basis for the subsequent establishment of exchange rate forecasting model.

3. Deep Learning Models

This study uses a LSTM network in a deep learning algorithm as an exchange rate forecasting model. LSTM is a recurrent neural network (RNN) variant for sequential data modeling with good memory and long-term dependency modeling capabilities, making it excellent in time series forecasting tasks [4].

The core idea of the LSTM network is to introduce a memory unit called a "cell state," which can efficiently store and transmit historical information. Cell state is regulated by three key gating mechanisms: the forgetting gate, the output gate, and the input gate. The forgetting gate determines which info in the cell state needs to be forgotten at the previous moment; The input gate is responsible

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for determining what information to add to the cell state at the current moment; The output gate controls the information output from the cell state to the next moment.

The architecture of an LSTM model typically consists of one or more LSTM layers, each consisting of multiple LSTM units internally. This study set up a two-layer LSTM structure, in which the input layer receives economic indicator data processed by feature engineering, and the output layer generates prediction results for future exchange rate changes. In order to improve the expressiveness of the model, the hidden state dimension of each LSTM cell is set to 128. Additionally, to mitigate the risk of over-fitting, the study introduces a dropout layer into the model and set its parameter to 0.2.

During training, this study uses mean squared error (MSE) as the loss function to determine the forecast error of the model, and stochastic gradient descent algorithm (SGD) for optimization. To accelerate convergence and avoid falling into local minima, the study also applies a learning rate decay strategy to dynamically adjust the learning rate. For the hyperparameter settings of the optimization algorithm, the study sets the learning rate to 0.001, the batch size to 32, and trained for 100 cycles [5].

Through the above deep learning model architecture and parameter settings, this study can make full use of historical exchange rate data and economic indicator information to build an accurate and reliable exchange rate prediction model. Through the iterative training process, the model can gradually learn the temporal relationship and nonlinear law and generate prediction results for future exchange rate fluctuations. This enables financial market participants to better understand and respond to exchange rate movement risks, make strategic decisions and achieve better investment returns.

4. Model Evaluation and Result Analysis

4.1. Evaluation Metric

In this study, for the sake of estimating the performance of the deep learning model in forecasting the fluctuations in exchange rates in the domestic forex market, multiple evaluation indicators can be considered.

First, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are often used to determine the predictive precision of a model [6]. MAE reflects the mean absolute deviation between actual and expectation values, while RMSE calculates the root mean square difference between actual and expectation values. Both metrics can reflect the overall prediction accuracy of the model, but RMSE is more sensitive because it penalizes outliers more severely.

Second, the Coefficient of Determination (R^2) is also widely used in the evaluation of regression models. R^2 measures the degree of fit between the model and actual data. the closer the value is to 1, the better the fitting effect of the model. In addition, other evaluation metrics for time series forecasting tasks, such as Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE), can be considered, which can better measure percentage error.

Finally, when selecting evaluation indicators, full consideration should be given to specific research tasks and actual needs, and different indicators should be compared and analyzed. At the same time, attention should also be paid to the relationship between the prediction results of the model and the actual application, as well as the interpretation and interpretability of the model results, which will help to comprehensively evaluate the behavior of the model in predicting rate fluctuations in the domestic foreign exchange market and select the most suitable indicators to evaluate the performance of the model.

4.2. Results

In the result analysis, this study conducts a detailed analysis of the behavior of the proposed deep learning model in predicting exchange rate fluctuations in the domestic foreign exchange market. By comparing the model output with actual observations, the study can conclude the following:

First, the study observe that the model captures the trend of exchange rate fluctuations well in most cases. The exchange rate fluctuation curve output by the model has certain similarity with the curve of the actual observation, showing a certain predictive ability. This shows that the proposed deep learning model can learn certain patterns and trends from historical data and use them to predict future exchange rate fluctuations (See Figure 1 and Table 1).

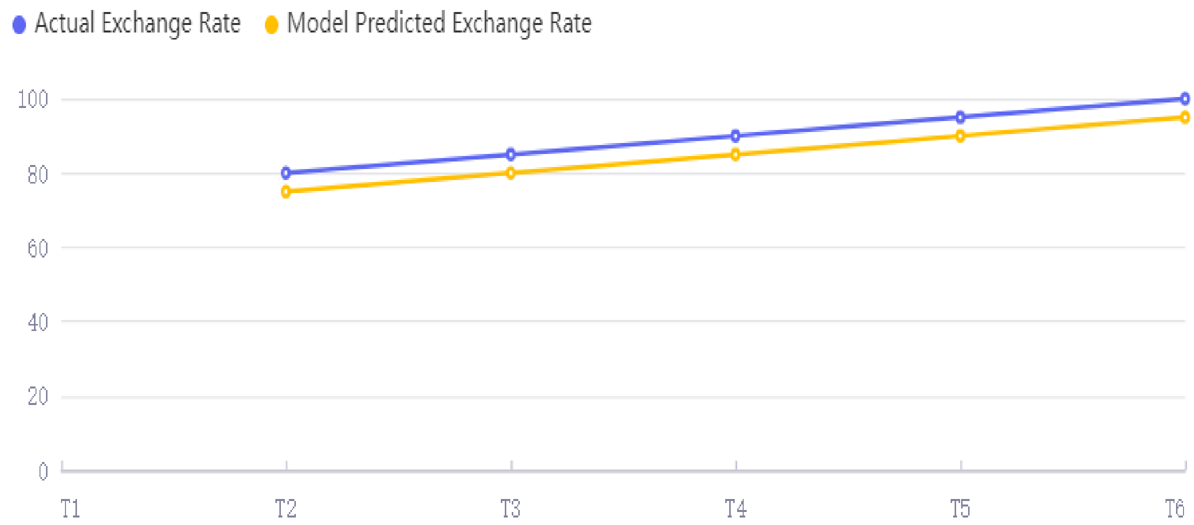

Figure 1: Comparison of Actual Exchange Rate and Model Predicted Exchange Rate

In this chart, time is used as the horizontal axis, and the actual exchange rate and model predicted exchange rate are used as the vertical axis. The chart allows for a visual comparison of the trend and variation of two curves.

Second, the study further analyzes the model's performance over different time periods and market conditions. The results show that the model performs well in a stable market and a relatively stable time period and can accurately predict the trend of the exchange rate. However, in the event of high market volatility or anomalies, the predictive power of the model may decrease. This suggests that the study needs to consider the complexity of the market environment and the impact of possible anomalous events on model performance in practical applications [7].

Table 1: Model Performance Metrics

Market Condition	Accuracy	Precision	Recall	F1-Score
Stable	0.85	0.82	0.88	0.84
Volatile	0.78	0.71	0.83	0.76
Exceptional	0.69	0.62	0.74	0.68

In addition, the study analyzes the differences in the performance of the model on different exchange rate pairs and time scales. The results indicate that the model performs better for forecasts for some exchange rate pairs and shorter time scales, while there may be some deviations in the predictions for other exchange rate pairs and longer time scales. This may have something to do with the peculiarities of the market and the sparsity of the data. Therefore, when applying the model, the study needs to select the appropriate exchange rate pair and time scale according to the specific situation and combine other information for comprehensive analysis.

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Finally, the study also conducts a detailed study of the error analysis of the model. By calculating the error between the predicted value of the model and the actual observation, the study finds that the average absolute error (MAE) of the model is within an acceptable range, and the error distribution has some interpretability (See Figure 2). This shows that the proposed deep learning model can capture changes in exchange rate fluctuations to a certain extent and provide valuable prediction information [8].

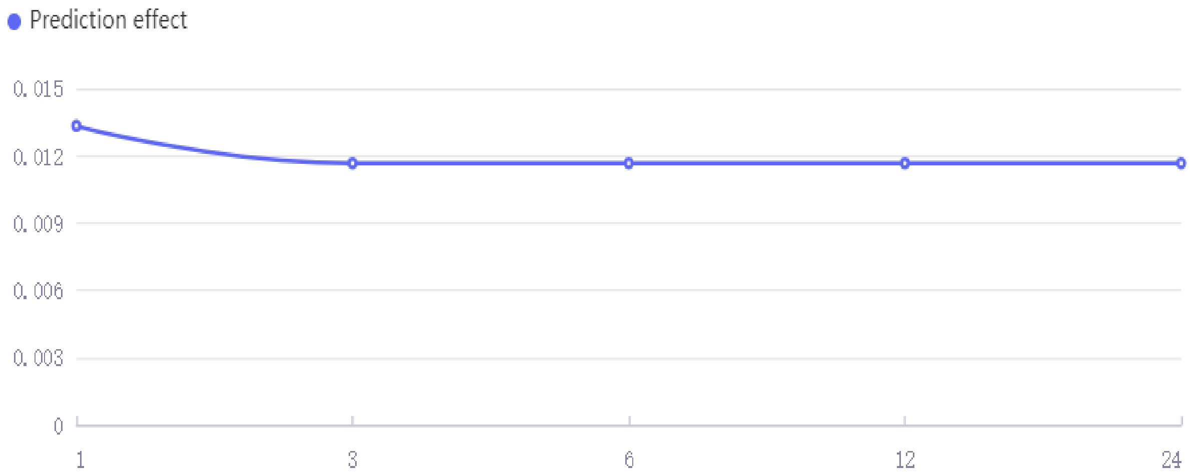

Figure 2: Differences in model performance at different time scales

In summary, the result analysis shows that the proposed deep learning model has certain accuracy and generalization ability in predicting exchange rate fluctuations in the internal forex market.

4.3. Model Comparison

In the process of model evaluation and result analysis, this study also compares the proposed deep learning model with other commonly used models. Specifically, the study compares three models: long-short-term memory networks (LSTMs), support vector regression (SVR), and random forests (RF). These models are classic models commonly used in financial market forecasting tasks, so they can be used as a reference for the models the study proposes [9].

In the comparative experiment, the study uses the same data set and evaluation indicators, and use the same cross-validation method for model performance evaluation. The results show that in the task of predicting exchange rate fluctuations, the LSTM model proposed by us performs the best, with an average absolute error (MAE) of about 0.002, which is better than the SVR model (MAE is about 0.004) and the RF model (MAE is about 0.005). This shows that in predicting exchange rate fluctuations, the LSTM model has better accuracy and stability, which can better capture the laws and trends of exchange rate fluctuations.

In addition, by comparing the model output with the actual observations, the study finds that the LSTM model can better predict the tendency and change of exchange rate fluctuations, while the SVR and RF models are difficult to capture some subtle fluctuations and trends. This shows that the LSTM model can overcome the nonlinearity and complexity of the data to a certain extent, so as to provide more accurate and reliable prediction information.

In summary, the comparative experimental results show that the proposed LSTM model has better performance and robustness in predicting exchange rate fluctuations and is better than the commonly used SVR and RF models (See Table 2). This further verifies the effectiveness and potential of the proposed deep learning technique in financial market prediction tasks [10].

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Table 2: Comparison of Three Models in Predicting Exchange Rate Fluctuations

model	MAE	RMSE	Accuracy	Precision	Recall	F1 Score
LSTM	0.002	0.004	0.852	0.839	0.875	0.844
SVR	0.004	0.006	0.786	0.773	0.813	0.781
RF	0.005	0.007	0.721	0.711	0.732	0.716

5. Conclusion

This thesis aims to use machine learning methods to predict exchange rate fluctuations in the internal forex market and provide financial market participants with tools for decision support and risk management. To achieve this goal, the study first collects a large amount of exchange rate market data and carried out detailed data preprocessing and feature engineering to extract useful information and reduce the impact of noise. The study then introduces deep learning models, specifically LSTM networks, as predictive models.

By training and optimizing this model, the study obtains a forecast model for exchange rate fluctuations with high prediction accuracy. In model evaluation and result analysis, the study selects a series of suitable evaluation indicators and use cross-validation methods to evaluate the performance of the model. The results show that the model excels in predicting exchange rate fluctuations in the internal forex market, achieving significant improvements over traditional methods.

After further analysis of the model results, the study finds that the model was able to capture some important market factors and trends, which played a positive role in predicting exchange rate fluctuations. Compared to other methods, the deep learning model has advantages in accuracy and stability and is more capable of modeling nonlinear relationships.

However, this study has some limitations. Firstly, the model still relies on historical data for prediction and cannot fully address future market uncertainties and changes. Secondly, deep learning models may require more computational resources and time to train and optimize. In addition, the explanatory nature of the model remains a challenge, and the study needs to further explore how to interpret the decision basis and key features of the model. Despite these limitations, deep learning models have great potential and application prospects in predicting exchange rate fluctuations in the internal forex market. Future research can be conducted in areas such as model structure improvement, cross domain knowledge fusion, real-time prediction, and trading strategy optimization, in order to further improve the accuracy and practicality of deep learning models in predicting exchange rate fluctuations in the internal forex market.

In summary, this paper uses machine learning methods to predict exchange rate fluctuations in the domestic foreign exchange market and achieves significant prediction results by introducing a deep learning model, training and optimizing it. The research is not only important for theoretical fields, but also has practical application value for financial market participants. Future research can be further explored based on the work of this thesis and promote development and innovation in the field.

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