Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 7s (2025)

Long- and Short-Term Memory Networks in Financial Market Predictions: A Study on USD Fluctuations

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Article History:

***Received:** 26-10-2024*

***Revised:**10-11-2024*

***Accepted:**18-12-2024*

Abstract:
The financial market is very sensitive to changes in the USD exchange rate. People may better assess the economic condition and steer clear of financial hazards with accurate predictions of the USD rate of exchange. This study proposes a CNN-STLSTM-AM hybrid method for closing USD price forecasting. A convolutional neural network (CNN) uses the input data to extract local characters. One better model suggested in the article, Specialized Tanh Long and Short-term Memory (STLSTM), uses local characters to predict the closing value of the USD exchange rate. The feature weights are distributed through the Attention Mechanism (AM) according to the effect of the localized character on the closing price. To prohibit total discarding or retention, the output range is altered from (0, to 0.2, 0.96). This is achieved by adding the tanh (x) plus 0.2 functions to the input gate. The following neural networks are examined and compared: SVR, CNN, CNN-LSTM, CNN-LSTM-AM, LSTM, GRU-LSTM, and CNN-STLSTM-AM, all of which predict the closing price. Experiments show that CNN-STLSTM to AM is the most accurate prediction model.

Keywords: Financial Market, Exchange Rate, LSTM, STLSTM, SVR.

1. Introduction

The importance of the exchange rate in the international financial market is growing as it impacts economies throughout the world [1]. Foreign commerce and national economic growth are both negatively impacted when the USD exchange rate volatility ranges beyond a certain level [2]. Researching accurate USD exchange rate forecasts is, hence, of paramount importance [3-5]. Investors may understand the right trading time and make more money if they correctly analyse the foreign exchange market [6]. From the government's perspective, accurate predictions of future exchange rates serve as a foundation for relevant administrative departments, aid in reallocating government resources [7], stabilize the financial market and alleviate economic pressures caused by extreme fluctuations in the exchange rate [8-10].

There are several features shared by the USD exchange rate [11], including long-term correlation, non-stationarity, uncertainty, and non-linearity. It is challenging to make good predictions with only one neural network [12-15]. So, to anticipate the USD exchange rate, this research proposes a CNN-STLSTMAM model. The data utilized for this paper's experiments include the USD rate of exchange from June 4, 2007, to Dec. 31, 2022, as well as the Dow Jones industrial average (DJIA), the closing prices of the Shanghai Composite Index (SCI) [16], the S and P global oil index [17], the gold spot (GS) and the USD index (USDI).

The STLSTM, AM, and CNN components form the model's core. By using CNN, the eigenvalues from the experimental data may be retrieved [18–20]. This study presents a new STLSTM approach [21] to improve the LSTM internal structure and better discover the link among eigenvalues [22]. AM is an appropriate mechanism for deducing the mapping connection between different types of data [23]. It is capable of capturing a huge number of eigenvalues and selecting the most important ones for the present job [24]. The CNN-STLSTM to AM is compared against the SVR [25], CNN network, GRU-LSTM, LSTM, CNNLSTM, and CNN-LSTM to AM in this study.

The main points of this article are these:

- An updated STLSTM model is suggested by enhancing the LSTM's interior structure. The function tanh plus 0.2 is used.
- Utilizing data from DJIA, SCI, GOI, GS and USDI, this research proposes a CNN-STLSTM-AM method to predict the USD exchange rate's closing price for the next trading day.
- This study uses experimental comparisons to examine the six exchange rate prediction methods, including the CNN-STLSTM-AM method. The CNN-STLSTM-AM model outperformed the others in terms of predicting accuracy and error rate, according to the findings of the experiments.

The following is the outline of the parts that make up this paper: Section 2 provides a literature survey to STLSTM, CNN-STLSTM to AM and AM. The research gap, experimental setup, procedures, information, data source of information, data preprocessing, parameters, findings, and analysis are presented in Section 3. Section 4 provides a concise summary of the paper's results and suggests directions for further research.

2. Literature Survey:

The use of Long Short-Term Memory (LSTM) networks has grown in importance for forecasting financial market movements, especially to simulate the US dollar's ebb and flow. Despite their widespread usage, traditional methods like as ARIMA and GARCH are often unable to capture the non-linear and temporal dynamics that are intrinsic to financial time series. These more conventional models have been surpassed by LSTMs because of their superior performance in retaining long-term dependencies and mitigating vanishing gradient concerns. Researchers have shown that by dynamically weighting important characteristics, hybrid models that combine LSTM with feature extraction approaches, such as Convolutional Neural Networks (CNN) or Attention Mechanisms (AM), greatly improve prediction accuracy. While GRU-LSTM and CNN-LSTM-AM are useful variants for simulating complicated market behaviours, because they rely on general activation functions, they aren't particularly flexible when it comes to financial information. The current state of LSTM-based techniques for USD exchange rate prediction might require some improvement, especially regarding domain-specific adaptations such as specialized activation functions or feature-enhancing processes. There is still a lot of potential for development in this area.

3. Research Gap

Several research gaps persist in adequately addressing the intricacies of USD exchange rate changes, despite the extensive use of Long- and Short-Term Memory (LSTM) networks in financial market prediction. The majority of the existing research makes use of traditional long short-term memory (LSTM) designs, which have a hard time capturing the complex features of currency rate data, including its non-linearity, non-stationarity, and long-term correlations. Despite the promising results of CNN-LSTM and attention-augmented variations and other hybrid models, there has been little effort to optimize these models with domain-specific improvements, such as specialized activation functions or techniques to handle financial time series more effectively. The integration of many economic indices, including the DJIA, SCI, and worldwide oil and gold indexes, using LSTM-based networks has also received limited attention. Emerging hybrid systems like CNN-STLSTM-AM, which may dynamically use spatial and temporal information, have also not been thoroughly compared. If these gaps are filled, models for anticipating USD exchange rate changes in unstable financial markets will be more accurate and easier to understand.

4. Methodology

4.1 A CNN-STLSTM-AM

Convolutional neural networks can aggregate and abstract local characteristics from input data into high-level eigenvalues. Following feature extraction, STLSTM can do time-series forecasting and track the long-term relationship of higher-level eigenvalues. The core principle of AM development is to exclude irrelevant data and concentrate on local data that significantly impacts the outcome. A CNN-STLSTM-AM model is constructed to predict the USD exchange rate based on the characteristics of CNN, STLSTM, and AM. Figure 1 shows the architecture of CNNSTLSTM-AM, which consists of the following layers: input, STLSTM, CNN, AM, and output. The CNN layer consists of two layers: the convolutional and the pooling.

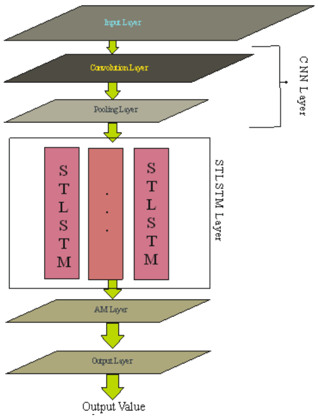

Figure 1 Architecture of CNNSTLSTM-AM

4.2 STLSTM

Time-series forecasting and natural language processing are two areas where LSTM has found extensive usage and achieved notable results. The "gate" structures and memory cells are the key components of long short-term memory. The input gate refreshes the memory cell while retaining some of the initial data from the present LSTM unit.

For each previous LSTM unit, the forget gate decides what input data to keep and what to discard. The value of the output gate is determined by the memory cell. The memory cell can instruct LSTM units to process the data. The internal structure of LSTM is enhanced by the new model STLSTM. By adjusting the output range of the input gate, STLSTM introduces the tanh plus 0.2 function, which guarantees the correctness of the input gate.

Figure 2 shows the STLSTM network architecture. The input gate data is almost entirely ignored by the sigmoid function for values close to 0, while values close to 1 are nearly entirely preserved and passed on. Before the enhancement, the output range is zero. With the addition of the tanh plus 0.2 function, the output range becomes (0.2, 0.96) and the values around 0 and 1 are approximated to 0.2 and 0.96, respectively. To get a relationship among time-series data, the function changes the output range of the input gate to a more specific range.

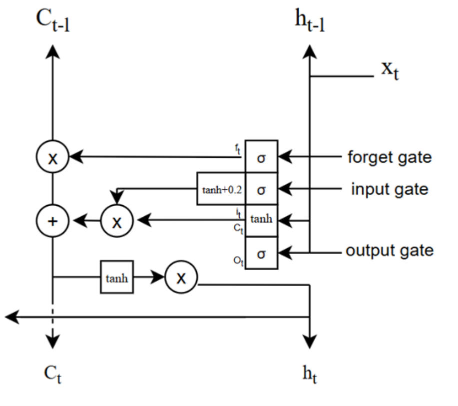

Figure 2 STLSTM Network Architecture

There are three pieces to the STLSTM unit's input data at time t: input data. x_t, output data h_{t-1}, and memory cell c_{t-1}. Simply put, the forget gate refreshes the memory cell after retaining or forgetting. x_t and h_{t-1}. The input gate selectively lets through the x_t and h_{t-1} Data that is necessary. To modify the output range of the input gate, STLSTM employs the tanh plus 0.2 function. The tanh function induces candidate memory cells by activating. h_{t-1} and x_t.

An applicant reminiscence cell, the result value of the input, the current memory cell, the previous memory cell, and the forget gate's output value are used to update the current memory cell. Lastly, the STLSTM's output is calculated by summing the current values of the output gates and memory cells.

The formulae for the calculations are as follows: (1) through (6).

$$f_t = \sigma\left(w_f \times [h_{t-1}, x_t] + b_f\right) \quad (1)$$

$$i_t = \tanh\left(\sigma(w_i \times [h_{t-1}, x_t] + b_i + 0.2\right) \quad (2)$$

$$\tilde{c_t} = \tanh\left(w_c \times [h_{t-1}, x_t] + b_c\right. \quad (3)$$

$$c_t = f_t \times c_{t-1} + i_t \times \tilde{c_t} \quad (4)$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \times \tanh(c_t) \quad (6)$$

The forget gate's bias (bf) and weight (w_f) determine its output value (f_t), which may take on values between 0 and 1. With the input gate's weight (w_i) and bias (b_i) set to the values, the output value (o) is obtained. The bias of a candidate memory cell is denoted by b_c, and its weight is w_c. Memory cell Ct at time t, with the output value of the gate o_t, which may be anywhere from zero to one. w_o denotes the weight of the output gate, whereas b_o Denotes its bias. "h_t" is the value that the STLSTM produces.

4.3 Attention Mechanism (AM)

AM has evolved from its original use in machine translation into a crucial component of neural networks. Time-series forecasting is only one of several areas where AM has found widespread use. The idea is that the human attention system might serve as an inspiration for AM. By giving higher importance to certain elements of the model, AM can extract more crucial information. If AM can optimize the model, it will be able to make better decisions. Figure 3 shows the structure of the AM method.

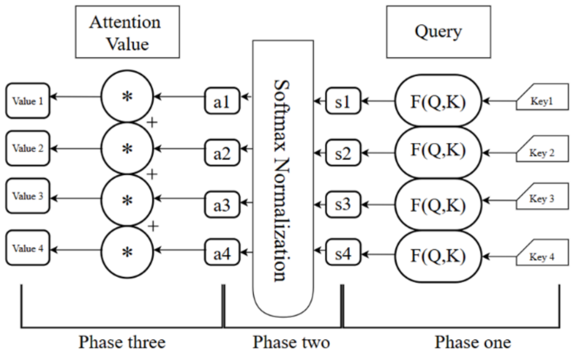

Figure 3 Structure of the AM Method

Here are the steps involved in AM:

Step 1: Function and compute mechanism introduction occurs initially. Query and Key allow one to compute the correlation. Equation (7) shows the formula.

$$s_i = Query \times Key_i \qquad (7)$$

Where Si stands for the connection.

Step 2: As seen in formula (8), the second step involves using SoftMax to transform the scores from the first stage.

$$a_i = Softmax(s_i) = \frac{e^{s_i}}{\sum_{j=1}^{L_x} e^{s_i}} \qquad (8)$$

Step 3: To get the Attention Value, they may use the weight coefficient from the second step and add it together, as stated in equation (9).

$$Attention\ value = \sum_{i=1}^{L_x} a_i \times Value_i \qquad (9)$$

The input vector is denoted by Value i.

5. Experimental Results and Analysis

This study demonstrates the efficacy of the CNN-STLSTM-AM method by comparing it to six base methods in a similar functioning situation, using identical training and test sets.

5.1 Experimental Setting

This setup has an Intel(R) Core (TM) i5-6300HQ CPU running at 2.30 GHz, 4.00 GB of RAM, and an NVIDIA GeForce GTX 960 M card based on graphics, and it is used to run Windows 10 operating system experiments. PyCharm 2020 1.3 x64 and Python 3.7.3 were the programming languages and compilers utilized throughout the studies. The deep learning framework used in the experimentations is Keras with TensorFlow.

5.2 The Experimental Procedure

Figure 4 shows the experiment flow diagram.

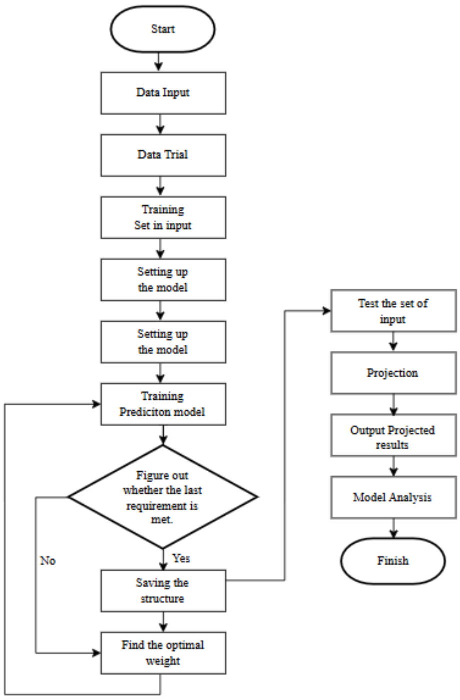

Figure 4 Experiment Flow Diagram

5.3 Data source

The Wind database supplies the data used in the experiments. Data utilized for the experiment comes from the following sources: the USD exchange rate, the lowest price, the greatest pricing, and the closing price from May 4, 2007, to December 31, 2022; GS, DJIA, GOI, and USDI.

5.4 Preprocessing Data

There seems to be some duplication or missing data in the experiment. The missing data is filled in by averaging the first two points of data in this study. Data duplication results in the deletion of earlier data. The size of data elements might vary greatly, and the values can also vary greatly from one another. Data analysis outcomes could be impacted by non-standardized data. Depending on their importance, data objects might vary greatly in size.

To account for variations in dimensions and value ranges across data items, experiments use data standardization. In order to make the data fit into a predetermined category, data standardization scales it proportionally. The Z-score standardization approach is used in this study. The Z-score-standardized data is uniformly distributed about zero, with a normal deviation of one. The standardization data won't be an issue because of how drastically different the data is. Here is the standardizing equation (10).

$$x^{\times} = \frac{x - \bar{x}}{\sigma} \qquad (10)$$

5.5 Experimental Parameters Setup

The input layer receives the standardized data. In a convolutional neural network, the data makes its way through two layers: the convolutional and the pooling. The convolutional layer uses filters within the layer to represent the output dimensions. The convolution layer's kernel Size is a measure of the convolution kernel's size. A convolution layer's padding is the filler used for the convolution process.

This research makes use of max pooling. Max pooling window size is best achieved by using a layer that pools the size.

For a pooling operation, the choice to fill the edge is known as pooling layer padding. The goal of the STLSTM optimizer is to get the parameters as close to the optimal value as possible. One parameter that governs the model's learning progress throughout iteration is the STLSTM learning rate, which is utilized to minimize the model's error. The choice to fill the edge for the convolution process is known as convolution layer padding. Max pooling is used in this study. The optimal size for the max pooling window is the pooling layer pool size. For a pooling operation, the choice to fill the edge is known as pooling layer padding.

The goal of the STLSTM optimizer is to get the parameters as close to the optimal value as possible. One parameter that governs the model's learning progress throughout iteration is the STLSTM learning rate, which is utilized to minimize the model's error. Iterations are represented by STLSTM Epochs. Incorrect selection of the value will lead to either overfitting or underfitting. The STLSTM batch size measures how many samples were collected for each training run. The optimal convergence accuracy of the model is achieved by using an appropriate STLSTM batch Size.

5.6 Results and Analysis of Experiments

This study verifies the CNN-STLSTM-AM's forecasting impact by comparing its predicted value with CNN, SVR, GRU-LSTM, CNN-LSTM, LSTM and CNN-LSTM to AM. In order to measure and compare the seven models' predicting accuracy, the experiments use RMSE, R-squared, MAE, and training time.

The first step is to train the training set using several methods. These methods include CNN, SVR, GRU-LSTM, LSTM, CNN-LSTM-AM, CNN-LSTM and CNN-STLSTM to AM. Data normalization is applied to the training set during processing. Two, the following trading day, the trained model predicts what the USD exchange rate will close at. Lastly, Figure 5 demonstrates the comparisons between the real and forecasted values.

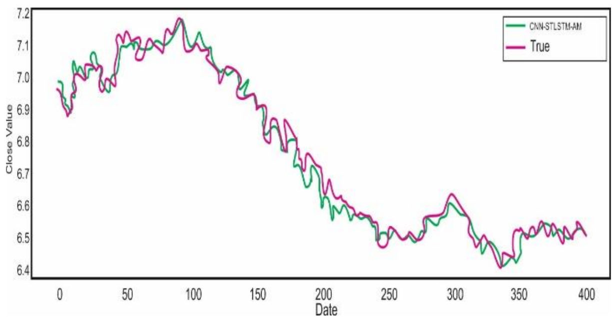

Figure 5 CNN or True Value STLSTM-AM Predicted Level

Out of the seven models for forecasting, CNN-LSTM-AM, CNN-STLSTM-AM, GRU-LSTM, LSTM, and SVR and CNN are in the order of the degree of match between the actual and predicted values. Among the models tested, CNN-STLSTM to AM has the best correct grade, meaning that its predicted value agrees with the actual price, whereas SVR has the worst. Each model's assessment indicators may be calculated based on the anticipated and real values. Figures 6–9 show the outcomes of the seven models' comparisons.

The least RMSE and MAE, the closest R^2 To 1, and the shortest training time of 19.0767 s are all shown in Figures 6–9. CNN-STLSTM-AM is the best model. According to the findings, CNN-STLSTM-AM outperforms SVR in terms of predicting accuracy. According to the findings, deep learning outperforms machine learning when it comes to time series forecasting. There is a 0.06%

improvement in R^2, a drop in MAE from 0.0225 to 0.0222, and an improvement in RMSE from 0.0302 to 0.0297 when using GRU-LSTM instead of LSTM. The results demonstrate that compared to LSTM, GRU-LSTM achieves better predicting accuracy.

In comparison to GRU-LSTM, CNN-LSTM achieves lower root-mean-squared errors (RMSE) and more accurate estimates (MAE) with an increase of 0.20 per cent (R^2) and a drop of 0.297 per cent (RMSE) and 0.2224 per cent (MAE), respectively. The findings demonstrate that LSTM's predicting accuracy may be enhanced by using its eigenvalues of the initial information collected by CNN. When comparing CNN-LSTM-AM to CNN-LSTM, we see a drop in RMSE, a decrease in MAE, and a gain of 0.26% in R^2.

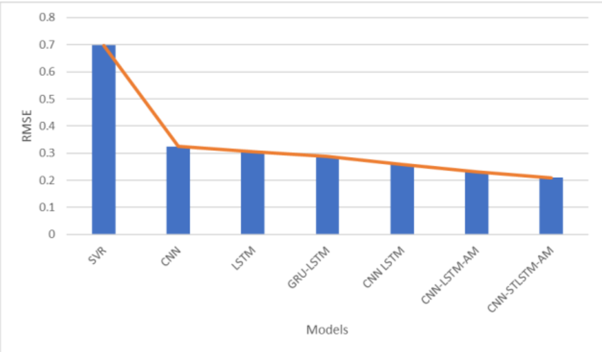

Figure 6 RMSE Comparison

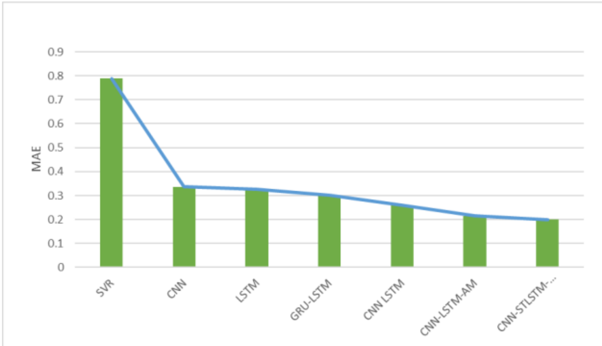

Figure 7 MAE Comparison

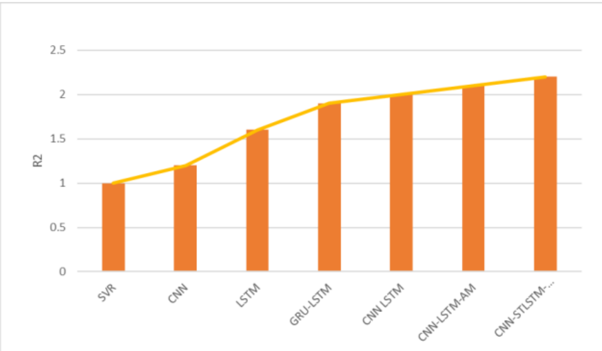

Figure 8 R^2 Comparison

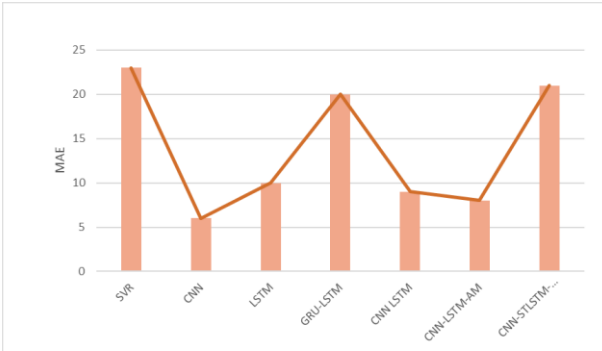

Figure 9 Comparison of Training Times

The results demonstrate that CNN-LSTM's forecasting accuracy may be enhanced by using the AM to assign matching weights to distinct eigenvalues. In comparison to CNN-LSTM-AM, CNN-STLSTM-AM has a reduced root-mean-squared error of 11.17%, an MAE of 15.88%, and an R^2 Of 0.20%. The findings demonstrate that STLSTM significantly enhances predicting accuracy. Starting with CNN-LSTM to AM and working this way down to SVR, GRU-LSTM, CNN-LSTM, CNN and LSTM are the method training times, in descending order of length.

The CNN-STLSTM to AM takes 19.0767 seconds to train, whereas the CNN takes 5.9840 seconds. While CNN STLSTM-AM does require more time, training the method only takes a single time and the time modification is less than 14 seconds, therefore it is okay to spend more time training as long as the prediction accuracy is good.

Results demonstrate that CNN-STLSTM-AM had the lowest predicting error out of the seven models tested. Relative Mean Square Error is 0.0216. There is an MAE of 0.0160. The duration of training is 19.0767 seconds. The CNN STLSTM to AM has the best-suited degree. An R^2 A value of 0.9932 is given. In terms of forecasting error and fitting degree, the CNN-STLSTM to AM outperforms the other six models. When it comes to predicting the USD exchange rate's closing price for the next trading day, CNN-STLSTM-AM is superior.

6. Conclusion

This article proposes a CNN-STLSTM to AM method for USD closing price forecasting. Using input data, CNN may derive eigenvalues. The recovered eigenvalues are learned using STLSTM, which improves the structure of LSTM and allows for improved discovery of the relationship among time-series data. Various eigenvalues are given appropriate weights by the AM. Compared to the other six models, CNNSTLSTM-AM outperforms them experimentally in terms of predicting accuracy and fitting degree. When compared to other models, this one has the shortest RMSE and MAE, the closest R^2, and the slowest training time. To predict the final value of the USD exchange rate, CNN-STLSTM-AM is a suitable model to use. In order to provide the prediction model with accurate information, the subsequent study will include quantifying SCI comment data using natural language processing technologies.

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