The 2nd International Conference on Multidisciplinary Engineering
(2nd ICOMDEN 2024)

The 2nd International Conference on Multidisciplinary Engineering: 00039 (2024) https://doi.org/10.29103/icomden.v2.xxxx
Volume 2, 2024
eISSN: xxxx-xxxx

Research Original Article

Application of Long Short-Term Memory (LSTM) Algorithm in Predicting Forex Trading Price Movements on the USD/JPY Pair

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Abstract

The foreign exchange (Forex) market offers the potential for high profits but also great risks through currency pair trading. This research proposes the use of the Long Short-Term Memory (LSTM) algorithm, a type of Recurrent Neural Network (RNN), to predict forex price movements for the USD/JPY (American Dollar to Japanese Yen) currency pair based on daily data over a two-year period. The model was designed with a "sequential" architecture consisting of two LSTM layers with 100 units each, followed by a Dropout layer to reduce overfitting and a Dense layer to generate predictions. The total model has 365,905 parameters, with 121,301 parameters trained. During training, model evaluation showed that the combination of batch size 16 and epoch 150 resulted in an RMSE of 0.9840, indicating high accuracy. The application of the model also resulted in an RMSE value of 1.04 and a MAPE of 0.56%, with an average accuracy of 99.44%, indicating a prediction accuracy that successfully follows the actual price trend and is effective in capturing forex price movement patterns in the USD/JPY currency pair, thereby supporting future trading decisions.

Keywords: Long Short-Term Memory (LSTM), Forex, USD/JPY Pair, Prediction

Introduction

In the era of advanced globalization, free trade continues to grow rapidly, driving increasingly competitive economic competition. This development is characterized by the rapid advancement of technology, especially in the field of information systems that have been transformed into internet media. This condition has encouraged many investors to actively participate in the capital market, which is now an important asset for companies around the world. One investment sector that is in high demand is foreign exchange (Forex) trading [1].

Forex is a currency trade between countries that takes place digitally on the global market for 24 hours. It involves the exchange of currency pairs, such as USD/JPY, which is one of the four most commonly traded currency pairs. The high volatility in the forex market offers great profit opportunities, allowing traders to profit from price movements through long (buying) or short (selling) positions [2]. However, high volatility also increases the risk of loss, making the ability to predict exchange rate movements an essential skill for traders [3].

In an effort to predict price movements in the forex market, data-driven methods play an important role. One method that is widely used for the analysis of time series data, such as forex prices, is Long Short-Term Memory (LSTM). As part of a Recurrent Neural Network (RNN), LSTM has the ability to remember patterns in sequential data and has proven to be effective in price prediction in various previous studies. The advantage of LSTM lies in its ability to learn historical patterns and utilize them to predict future price movements [4]. This research focuses on predicting the price of the USD/JPY currency pair using LSTM, given the importance of this currency pair in global forex trading. Previous research shows that the LSTM model is able to produce accurate price predictions on various currency pairs, so it is interesting to implement it on the USD/JPY pair [5].

Research conducted by Angel Joanna Wijaya, Windra Swastika, and Oesman Hendra Kelana focused on predicting the price of the EUR/USD and GBP/USD currency pairs using the Long Short-Term Memory (LSTM) method. The results showed that the best model for EUR/USD produced the lowest Mean Squared Error (MSE) of 0.0469 with a 1 layer LSTM configuration consisting of 10 nodes and using 5 inputs. Meanwhile, for the GBP/USD currency pair, the best model showed an MSE of 0.0520 with the same setup but using 3 inputs. Based on these findings, the researchers recommend using 5 inputs for EUR/USD prediction and 3 inputs for GBP/USD in practical applications [6].

Meanwhile, research by Michael Owen, Vincent, Riama Br Ambarita, and Evta Indra examined the implementation of the Long Short-Term Memory (LSTM) method in predicting gold price movements. On days 50, 100, and 150, the price predictions generated by the LSTM model were close to the actual price, with actual data of $118.86, $113.44, and $115.74, respectively, and predictions of $119.42, $114.67, and $115.97. These results show that closing price predictions made using LSTM have very good accuracy, with minimal differences between actual and predicted values [7].

Based on the description above, the authors are interested in conducting research with the title "Application of the Long Short-Term Memory (LSTM) Algorithm in Predicting Forex Trading Price Movements on the USDJPY Pair". This study aims to design and implement a forex price movement prediction system on the USD/JPY currency pair using the Long Short-Term Memory (LSTM) algorithm and evaluate the performance of the model to find out how well LSTM predicts price changes in the forex market.

Literature Review

1. Trading Forex

Forex (Foreign Exchange) is a 24-hour global market for currency trading, involving currency pairs such as EUR/USD and USD/JPY. The market has high liquidity, significant volatility and is influenced by economic news and global events. Its unique characteristics include the use of leverage and sharp price fluctuations, offering great opportunities but also high risks. Analysis in forex is divided into technical, fundamental and sentiment, which help traders understand price movements to make better trading decisions [8].

2. USD/JPY Pair

USD/JPY is one of the major currency pairs in the Forex market that is very actively traded. Combining the United States Dollar (USD) with the Japanese Yen (JPY), this pair has high liquidity and is often used by traders in various trading strategies. USD/JPY ranks second only to EUR/USD in international trading volume, demonstrating its importance in the currency market. The pair shows the amount of Japanese Yen required to buy one American Dollar. For example, if the USD/JPY rate is 110, then 110 Yen are needed to buy one Dollar [9].

3. Forecasting

Forecasting is a method that uses historical data to predict what will happen based on current and past situations and conditions. The perspectives on forecasting methods are very diverse from the views of each group of scientific methods adopted to make decisions. The forecasting method will produce an estimate of the future forecast and the basis for sound business planning and decisions. Since all organizations face an unknown future, actual future demand is expected [10].

4. Deep Learning

Deep learning is a branch of machine learning that uses a series of non-linear transformation functions arranged in deep layers to build high-level abstraction models on data. It is highly effective in extracting complex patterns, especially on large and complicated datasets. The advantages of deep learning make it capable of tackling problems in various fields, such as image recognition, natural language processing, speech recognition, medical image processing, as well as prediction in various industries [11].

5. Long Short-Term Memory (LSTM)

LSTM is a neural network derived from Recurrent Neural Network (RNN) designed to overcome the vanishing and exploding gradient problems in conventional RNNs, which often impede the learning of long-term dependencies. LSTM has three main layers: an input layer, a hidden layer containing LSTM cells, and an output layer. Each cell is equipped with a cell state, which allows important information to be stored from one time step to the next, maintaining long-term information stability. Inside each LSTM cell, there are three important gates: forget gate, input gate, and output gate. The forget gate controls which information from the previous cell state needs to be kept or discarded, the input gate determines which new information needs to be kept, and the output gate decides which information to use for prediction [12]. The combination of these gates makes LSTM more efficient in handling complex sequential data than conventional RNN.

1. *Forget Gate*

$$f_t = \sigma\left(W_f S_{t-1} + W_f X_t\right) \tag{1}$$

2. *Input Gate*

$$i_t = \sigma(W_i S_t + W_i X_t) \tag{2}$$

3. *Cell State Update*

$$c_t = (i_t * \tilde{C}_t + f_t * c_{t-1} \tag{3}$$

4. *Output Gate*

$$O_t = \sigma(W_o S_{t-1} + W_o X_t) \tag{4}$$

$$h_t = O_t * tanh\ (C_t) \tag{5}$$

6. Evaluasi

Evaluation metrics are used to measure the difference between observed and predicted values, with the aim of minimizing the prediction error. They also facilitate comparison of model performance so that the best model can be selected. In addition, analysis of the residual pattern (difference between predicted and actual values) helps identify potential biases in the model. RMSE (Root Mean Squared Error) measures the deviation between the prediction and the actual value, with the smaller the RMSE value indicating better model performance. MAPE (Mean Absolute Percentage Error) calculates the average percentage error between the prediction and actual values, where a smaller MAPE value indicates a more accurate model [13].

1. *Root Mean Square Error* (RMSE)

$$\sqrt{\frac{1}{n}\sum_i^n(\tilde{y}_i - \tilde{y}_1)^2} \tag{6}$$

2. *Mean Absolute Percentage Error* (MAPE)

$$100 \times \sum_{i=1}^n \left|\frac{\tilde{y}_i-\tilde{y}_i}{y_i}\right| \tag{7}$$

Materials & Methods

1. Research Methodology

This research uses the waterfall method, which is a system development model with sequential and systematic phases, where each stage must be fully completed before proceeding to the next stage. This model provides structure and tight control over each phase of development. The stages of research that will be carried out are as follows:

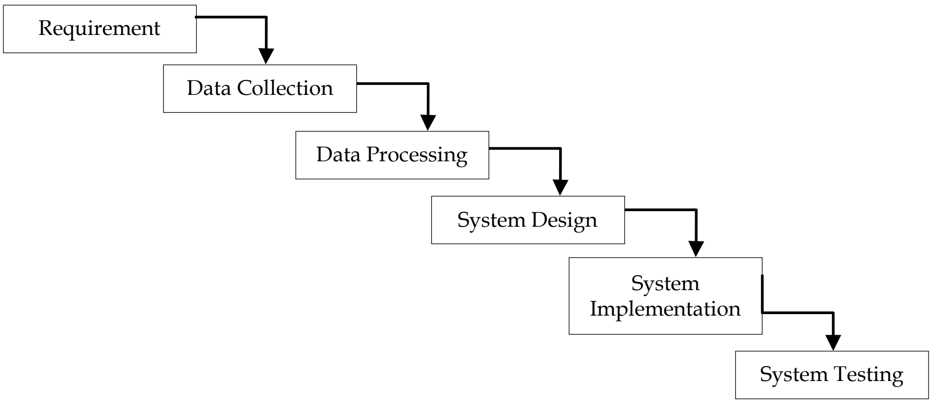

Figure 1. Research Methodology

a. Requirement

The requirement stage includes problem identification through initial research to formulate the research focus, namely USD/JPY forex price prediction with the LSTM method. Literature study is then conducted to collect theories and references that support the solution of this problem.

b. Data Collection

This research uses primary data from yahoofinance.com in CSV format with daily time frames for USD/JPY from July 2022 to July 2024. The data was standardized and then divided into 80% training data and 20% test data. Training data is used to train the LSTM model, and test data to measure the performance of the model.

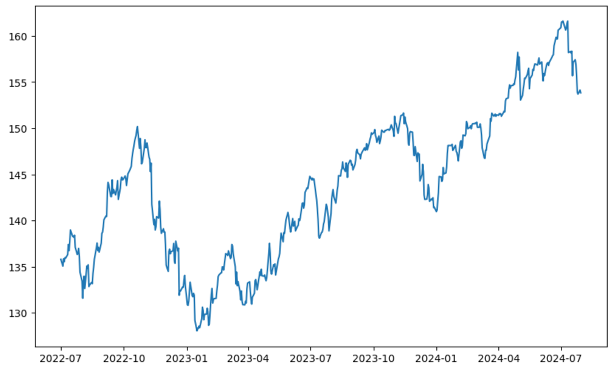

Figure 2. Dataset Visualization

The USD/JPY forex price movement visualization chart July 2022-July 2024 gives a clear picture of the complex dynamics in the forex market.

c. Data Processing

Data processing is done on Google Colab using Python libraries such as pandas, NumPy, matplotlib, scikit-learn, and TensorFlow. This stage aims to analyze, manipulate, visualize, and prepare data for machine learning models.

d. System Design

The system is designed using Data Flow Diagram (DFD) to describe the application processes efficiently, guiding the implementation with the appropriate programming language.

e. System Implementation
At this stage, the application is built with the Python programming language based on the design that has been made.

f. System Testing
The final stage includes testing the performance, functionality, and stability of the system to ensure the application works as planned, including trials and bug identification.

2. System Scheme

The scheme for the prediction system for forex trading price movements on the USD/JPY pair using the Long Short-Term Memory (LSTM) method is as follows:

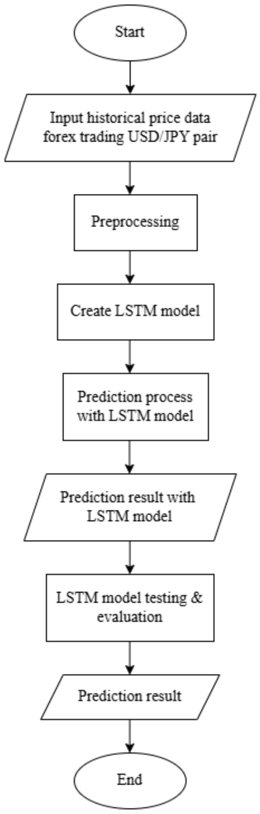

Figure 3. System Scheme

The initial process of forming the algorithm scheme in the system begins with inputting historical data of USD/JPY forex prices from yahoofinance.com, with a daily time span from July 2022 to July 2024. The next stage is preprocessing, which includes data sorting and removal of irrelevant attributes. In data cleaning, researchers dealt with missing values, noise, and inconsistencies to ensure data quality. After that, the data was normalized using min-max scaling and divided into training data (80%) and testing data (20%). Next, the LSTM model is developed by determining parameters such as hidden layer, neurons, learning rate, drop out, as well as various combinations of batch size (16, 32, 64, 128) and number of epochs (50, 100, 150, 200). In the prediction stage, the data passes through the gate mechanism in LSTM, which includes the calculation of forget gate, input gate, cell state, cell state update, and output gate. The prediction results of the LSTM model are evaluated using test data with the RMSE metric for error estimation and MAPE to evaluate the error relative to the actual value. The last stage is to display the prediction of USD/JPY forex price movements generated by the LSTM model.

Results and Discussion

This study aims to test the effectiveness of the Long Short-Term Memory (LSTM) algorithm in predicting price movements in the USD/JPY currency pair in the Forex market, which is known to be dynamic and experience rapid price changes. The LSTM algorithm was chosen for its ability to process long sequences of data as well as its ability to recognize hidden patterns in historical data, making it well suited for price movement analysis in Forex trading. This research was conducted in Google Colab environment with Python programming language to optimize data processing and implementation of Long Short-Term Memory (LSTM) model in predicting Forex prices. Google Colab was chosen because it provides access to important libraries such as TensorFlow and Keras, which support deep learning modeling, and enables real-time collaboration between researchers. These features facilitate experimentation and model evaluation with high efficiency. The Following is a table of datasets used in the study.

Table 1. Dataset Table

Date	Adj Close	Close	High	Low	Open
2022/07/1	135.785995	135.785995	135.977005	134.796005	135.785995
2022/07/4	135.042999	135.042999	135.770996	134.798004	135.042999
2022/07/5	135.839996	135.839996	136.345001	135.554993	135.839996
2022/07/6	135.520996	135.520996	135.962006	134.975006	135.520996
2022/07/7	135.966003	135.966003	136.203995	135.570007	135.966003
…	…	…	…	…	…
…	…	…	…	…	…
2024/07/25	153.891006	153.891006	154.151001	151.966995	153.891006
2024/07/26	153.697006	153.697006	154.731003	153.261993	153.697006
2024/07/29	154.139008	154.139008	154.337006	153.063004	154.139008
2024/07/30	153.832993	153.832993	155.190002	153.656006	153.832993
2024/07/31	152.669998	152.669998	153.580994	149.664001	152.669998

The first step in the process involved importing various libraries required to facilitate the creation, training, evaluation, and visualization of the model. Next, the dataset used was the historical data of the USD/JPY currency pair, which was imported into Google Colab from Yahoo Finance and covered daily trading prices from July 1, 2022 to July 31, 2024. After that, data processing is carried out through several important steps, including preprocessing, data normalization, data preparation, and data sharing, so that the data is ready to be used to build accurate prediction models, which can seen in table 2 below.

Table 2. Division of Training and Test Data

Target	Training Data	Test Data
Close Price	80%	20%

The Long Short-Term Memory (LSTM) model was developed at Google Colab by utilizing TensorFlow and Keras libraries, which allow flexibility and efficiency in the machine learning process. In this stage, researchers set various important parameters, including the number of neurons in the layer, activation function used, learning rate, batch size, and number of epochs. To optimize the performance of the model, various combinations of batch sizes, namely 16, 32, 64, and 128, as well as epochs varying between 50, 100, 150, and 200, were tested. In addition, a dropout technique was applied to prevent overfitting, ensuring that the model not only works well on the training data but can also generalize to data that has never been seen before. The model structure consists of two interconnected LSTM layers and is compiled using Adam's optimizer, which is known to be effective in accelerating convergence. Model evaluation is performed using metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to assess the accuracy of the resulting predictions. The best results were obtained using batch size 16 and epoch 150, which resulted in an RMSE of 0.9840, which can be seen in table 3 below.

Table 3. Evaluation results of LSTM model Combination

Epoch	Batch Size	RMSE	MAPE
50	16	1.3001	0.7118%
	32	1.1918	0.6325%
	64	0.9840	0.5193%
	128	1.2675	0.6724%
100	16	1.3382	0.7275%
	32	1.2224	0.6709%
	64	1.2032	0.6850%
	128	1.3466	0.7477%
150	16	1.4883	0.8215%
	32	1.4887	0.8027%
	64	1.3499	0.7130%
	128	1.3809	0.7542%
200	16	1.5845	0.8535%
	32	1.5380	0.8230%
	64	1.4744	0.8188%
	128	1.3854	0.7310%

The summary structure of this model is designed using a sequential architecture consisting of several main layers. The first layer is an LSTM with 100 units, which has 40,800 parameters to capture patterns in the data in depth. This layer is followed by a Dropout layer that serves to reduce overfitting without increasing the number of parameters. Next, there is a second LSTM layer with 100 units and 80,400 parameters, which plays a role in strengthening the model's ability to recognize more complex data sequences. Finally, the Dense layer produces one prediction output with 101 parameters.

Overall, the model has 363,905 parameters, of which 121,301 are trained parameters.

After completing the modeling process and selecting the best parameter combination based on RMSE evaluation, the Long Short-Term Memory (LSTM) model is tested using test data to assess its performance in real situations. At this stage, the predicted data is returned to its original scale, ensuring that the calculations performed are relevant to the actual values. The evaluation results show that the RMSE value reaches 1.04, which indicates that the deviation between the predicted and actual values is quite small, suggesting that the model is capable of producing accurate predictions. In addition, the Mean Absolute Percentage Error (MAPE) value of only 0.56% indicates a very low prediction error rate, which further strengthens the accuracy of the model. With an average accuracy of 99.44%, the model performs very well in predicting price movements in the test data. This performance not only confirms the reliability of the LSTM model, but also demonstrates its ability to capture complex patterns in the training data and deliver robust results on never-before-seen data.

Figure 4. Prediction Result Visualization Chart

The chart above shows the predicted price of the USD/JPY currency pair based on historical data and the prediction model. The black line represents the training data, which is the historical data used to train the model until the beginning of 2024. After this period, the blue line shows the actual USD/JPY price, while the red line shows the price prediction generated by the model. Both lines (blue and red) tend to move almost simultaneously, indicating that the prediction model is quite accurate in following the actual price pattern. In general, the chart shows price fluctuations from 2022 to early 2023, followed by an upward trend until early 2024, and a slight decline after April 2024. The model is able to capture similar patterns of price increases and decreases, although there are some small deviations at certain points, possibly due to unforeseen external factors. These charts show that the prediction model used is reliable enough to help traders understand future price trends and support trading decisions.

Conclusions

Based on the results, the researchers concluded that the LSTM model can successfully predict the USD/JPY forex price. During training, various combinations of batch size (16, 32, 64, 128) and number of epochs (50, 100, 150, 200) were tested, with the model using 100 hidden units and optimized with Adam's algorithm. It was found that the use of batch size 16 with 150 epochs resulted in an RMSE of 0.9840, demonstrating excellent prediction accuracy and creating an optimal balance between training and curation efficiency. The application of this model provided highly optimized results, with an RMSE value of 1.04 and MAPE of 0.56%, and an average accuracy of 99.44%. The predictions successfully followed the actual price trend, and the visualization of the results showed that the model could capture the price movement patterns, thus helping to understand the price trend and support future trading decisions.

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