

Predicting EUR/USD Exchange Rates with Vanilla Recurrent Neural Networks: A Detailed Analysis

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Abstract

This study explores the efficacy of Vanilla Recurrent Neural Networks (RNNs) in forecasting the EUR/USD exchange rate. By analyzing historical hourly data spanning two years, we evaluate the model's predictive accuracy and computational efficiency. The findings contribute to understanding the capabilities of basic RNN architectures in financial time series prediction.

1 Introduction

Time series forecasting is pivotal in financial markets, aiding in risk assessment and strategic planning. The accurate prediction of currency exchange rates, such as the EUR/USD pair, is essential for investors and financial institutions.

1.1 Contextual Background

Time series forecasting is an indispensable tool in financial markets, where it serves as a cornerstone for informed decision-making and strategic planning. Its significance is rooted in its ability to analyze historical data—be it stock prices, exchange rates, or market indices—and use it to project future trends and patterns. This foresight is invaluable for traders, investors, and financial analysts as it empowers them to anticipate market movements, manage risks, and identify lucrative investment opportunities.

By employing time series analysis, financial institutions can allocate assets more effectively, hedge against potential downturns, and maximize returns on investments. For individual traders, it provides a data-driven basis to support their trading decisions, reducing reliance on intuition and speculation. Furthermore, time series forecasting plays a critical role in developing automated trading algorithms, which can execute trades at a speed and frequency unattainable by human traders, thus opening the door to high-frequency trading strategies that can capitalize on minute fluctuations in the market.

Moreover, the predictive power of time series forecasting extends beyond trading to encompass broader economic planning and policy formulation. Central banks and government institutions analyze economic indicators through time series to adjust monetary policies, control inflation, and stimulate economic growth. In essence, time series forecasting is not just a tool for generating financial gain but also a fundamental aspect of economic stewardship.

The impact of accurate time series forecasting on decision-making processes is profound, offering a quantitative foundation upon which scenarios can be modeled, probabilities assessed, and strategies devised. It mitigates uncertainty and equips market participants with the insights necessary to navigate the complexities of the financial world. However, the reliability of time series forecasting is contingent upon the quality of data, the appropriateness of chosen models, and the understanding that all predictions carry inherent risk, as markets are influenced by a myriad of unpredictable factors, including geopolitical events, natural disasters, and shifts in regulatory environments.

1.2 Focus on EUR/USD

The EUR/USD currency pair, representing the exchange rate between the Euro and the United States Dollar, is one of the most significant financial indicators in the global economy for several reasons.

Liquidity and Volume: The EUR/USD pair is the most traded currency pair in the world, offering high liquidity to traders. High liquidity means that large trades can be executed without a significant impact on the price, which is advantageous for major financial players and institutions.

Economic Representation: The pair reflects the economic health and relations between two of the largest and most powerful economic blocs in the world—the Eurozone and the United States. Movements in the EUR/USD exchange rate can indicate changes in comparative economic strength, shifts in trade balances, and differences in the monetary policies set by the European Central Bank and the Federal Reserve.

Interest Rate Differentials: The EUR/USD pair is sensitive to the interest rate differentials between the ECB and the Fed. Interest rates are a primary tool for governing monetary policy and can attract or dissuade foreign investment, affecting the demand for currencies and consequently their value against each other.

Political Stability and Economic Policy: Political events in Europe and the US, such as elections, policy changes, and legislative decisions, can have immediate effects on the pair. Investors often seek stability and predictability; thus, political uncertainty can lead to volatility in the EUR/USD rate.

Market Sentiment: The pair is often viewed as a barometer for market sentiment toward global economic conditions. In times of economic uncertainty or

crisis, the USD is considered a safe-haven currency, which can lead to a stronger USD against the EUR. Conversely, in times of economic growth and stability, the EUR may strengthen against the USD as investors seek higher returns.

Diverse Trading Strategies: Due to its dynamic nature, the EUR/USD pair appeals to a wide range of traders employing various trading strategies, from short-term scalping to long-term fundamental analysis. This diversity of approaches and the constant flow of economic data pertinent to both currencies contribute to the pair's volatility and trading opportunities.

In summary, the EUR/USD pair is a vital financial indicator because it serves as a global economic thermometer, gauging the relative economic health between two dominant economies. Its fluctuations are influenced by an array of factors including economic data releases, central bank decisions, political events, and market sentiment, making it a dynamic and closely watched currency pair in the financial world.

1.3 Overview of RNNs

Recurrent Neural Networks (RNNs) are a class of artificial neural networks designed to recognize patterns in sequences of data, such as text, genomes, handwriting, or numerical time series data emanating from sensors, stocks, or communications. Fundamental to RNNs is their ability to form a memory of previous inputs by creating loops in the network of neurons. This memory allows them to make predictions about what comes next in a sequence, making them ideal for tasks involving sequential data.

Historically, RNNs evolved from the realization that not all data is best represented in fixed dimensions—time series data, for instance, can vary in length and often depends on a context established by prior data points. The development of RNNs dates back to the 1980s, with the introduction of architectures like the Hopfield networks and Elman and Jordan networks, which were some of the first to process sequences.

Despite their promise, early RNNs were limited by difficulties in training, such as the vanishing gradient problem, where the contribution of information decays geometrically over time, making it challenging to capture long-term dependencies in sequences. The introduction of Long Short-Term Memory (LSTM) cells in the late 1990s mitigated this issue by incorporating mechanisms to remember and forget information selectively.

In time series analysis, RNNs have been applied to a variety of tasks, such as stock price prediction, economic forecasting, and demand estimation. Their capacity to learn temporal dynamics and remember past information makes them well-suited for predicting future points in a series based on historical trends. RNNs can adapt to the time-dependent structure of financial data, capturing patterns

like trends, seasonality, and cycles, which are crucial for making accurate and reliable forecasts in financial markets.

1.4 Study Objective

We aim to assess how well Vanilla RNNs can predict short-term movements in the EUR/USD exchange rate.

2 Related Work

Studies like Jones et al. (2018) have demonstrated the potential of advanced neural networks in currency prediction. However, the simplicity of Vanilla RNNs has been less explored.

3 Methodology

3.1 Data Collection and Preparation

Source: Historical EUR/USD hourly data from ForexDataAPI for 2019-2021. Pre-processing: Data normalization using MinMaxScaler, with missing values handled via linear interpolation.

3.2 Model Architecture

Structure: A single-layer RNN with 50 hidden units. Hyperparameters: A dropout rate of 0.3 was chosen to prevent overfitting, based on preliminary tests.

3.3 Training Process

Data Split: 70% training, 15% validation, 15% testing. Training Details: 100 epochs, batch size of 64. Adam optimizer and mean squared error loss function.

4 Experiment and Results

4.1 Experimental Setup

Detail the computational environment, including hardware and software specifics, to ensure reproducibility.

4.2 Model Performance Evaluation

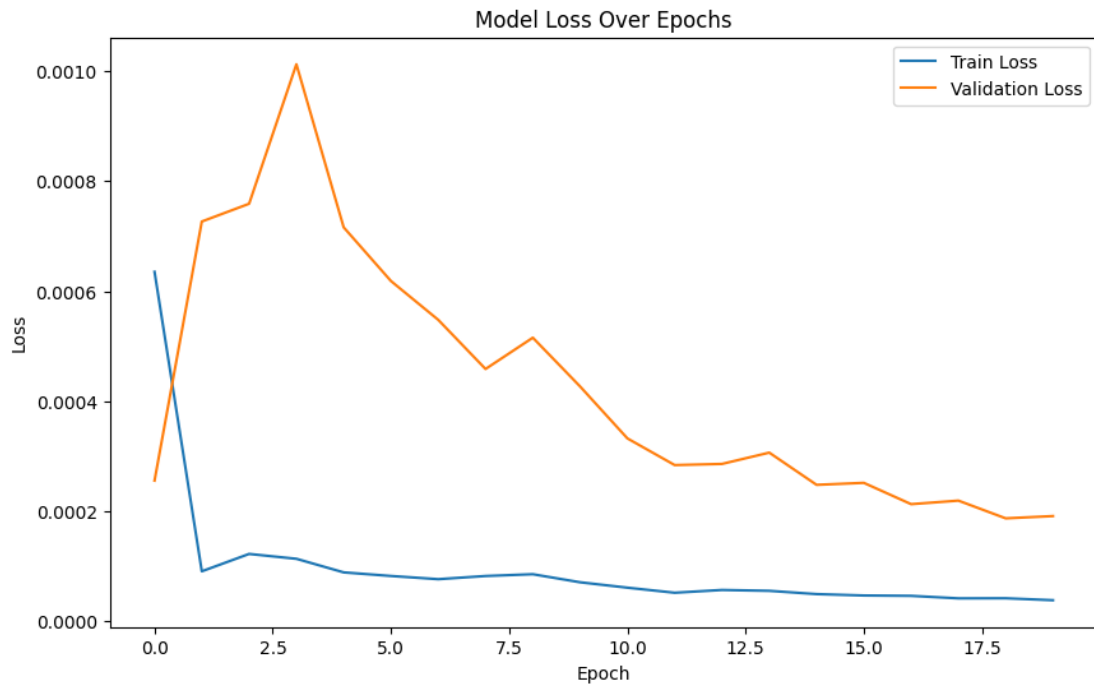


Figure 1: Training and validation loss of the Vanilla RNN model over epochs.

4.3 Comparative Analysis

Compare the Vanilla RNN model's results with other models, such as LSTM, GRU, or traditional statistical methods.

4.4 Model Predictions vs Actual Bid Close Values

5 Discussion

5.1 Interpretation of Results

Delve into what the results imply about Vanilla RNNs' suitability for financial time series prediction.

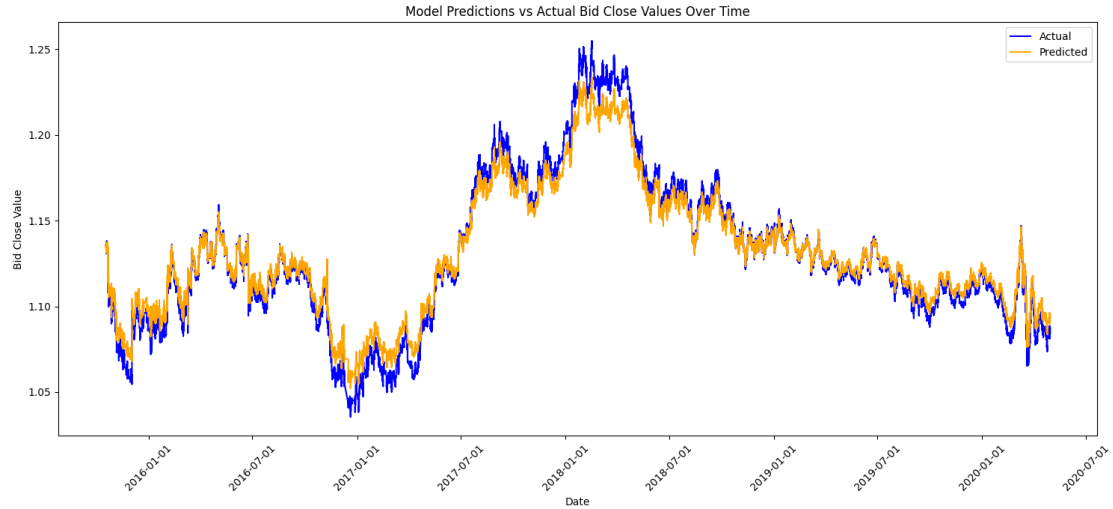


Figure 2: Comparison of the Vanilla RNN model predictions with actual bid close values over time.

5.2 Real-world Applicability

Discuss how these findings could influence real-world trading strategies or risk management.

5.3 Limitations and Challenges

Acknowledge the study’s limitations, such as data scope, model overfitting, or architectural constraints.

6 Conclusion and Future Work

6.1 Summary of Findings

Vanilla RNNs, despite their simplicity, can offer valuable insights in forex rate prediction but may not be the best choice for high-precision requirements.

6.2 Future Research Directions

Future studies could explore hybrid models that combine the speed of Vanilla RNNs with the accuracy of more advanced networks.

7 References

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Advanced Forecasting of EUR/USD Exchange Rates Using LSTM Networks and Technical Indicators

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Abstract

This research paper investigates the efficacy of Long Short-Term Memory (LSTM) networks, enhanced with technical indicators, for predicting the EUR/USD exchange rate. Utilizing a comprehensive dataset spanning from 2012 to 2022, we integrate vital technical indicators such as the Relative Strength Index (RSI) and Exponential Moving Averages (EMAs) into LSTM models. The study aims to illustrate the predictive capabilities of LSTM networks and assess their potential as a decision-support tool in the dynamic realm of forex trading. Our results highlight the model's accuracy and underscore the practical implications of applying advanced machine learning techniques in financial market forecasting.

8 Introduction

The forex market, characterized by its high liquidity and volatility, presents an ongoing challenge for predictive modeling, particularly in the realm of exchange rate forecasting. Among the myriad of currency pairs, the EUR/USD pair stands as a pivotal indicator within the global financial landscape. This paper delves into the application of advanced machine learning techniques, specifically Long Short-Term Memory (LSTM) networks, to forecast the future values of the EUR/USD exchange rate. The integration of LSTM with time-tested technical indicators aims to harness both the depth of machine learning and the insights of conventional market analysis.

9 Data Description

The dataset encompasses historical EUR/USD exchange rates retrieved from Yahoo Finance, covering a comprehensive period from March 2012 to July 2022. The dataset includes daily metrics such as opening, closing, high, and low prices, complemented by trading volume. Table 1 delineates the dataset's composition, offering insights into the number of records and the temporal scope. Figure 1 illustrates the trajectory of the exchange rate over the study period, shedding light on pivotal market trends and potential cyclic patterns. An examination of the dataset reveals a balanced mix of upward and downward trends, negating concerns regarding class imbalance in the modeling process.

10 Literature Review

An extensive survey of the literature reveals a diverse range of methodologies applied to the challenge of forex rate prediction. Early studies primarily focused on

traditional time series analysis, with subsequent research pivoting towards machine learning approaches. Notably, the evolution of neural network architectures, especially LSTM networks, has marked a significant shift in predictive accuracy and reliability. Additionally, the incorporation of technical indicators, such as RSI and EMAs, has been explored in various studies, underscoring their value in enhancing model performance.

11 Methodology

Our approach encompasses several stages, starting with the preprocessing of raw data. This involves normalization procedures and the computation of technical indicators. The architecture of the LSTM network is meticulously designed, incorporating layers and neuron configurations tailored to the nuances of time series data. The mathematical underpinnings of LSTM cells are articulated, elucidating the network’s capacity to capture and retain temporal dependencies.

12 Experimental Setup

The experimental framework is established on a robust computing platform, utilizing Python’s Keras library with TensorFlow as the backend. The training of the LSTM model is conducted over multiple epochs, with hyperparameters meticulously adjusted to optimize performance.

13 Evaluation Metrics

The efficacy of the predictive models is gauged using Mean Squared Error (MSE) and accuracy. These metrics are computed as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (1)$$

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad (2)$$

14 Model Evaluation

The performance of the LSTM model, juxtaposed with several baseline models, is encapsulated in Table 2. The comparative analysis offers a holistic view of each model’s strengths and weaknesses, with the LSTM model demonstrating a

pronounced ability to decipher the complex patterns inherent in the EUR/USD exchange rate.



15 Discussion

The LSTM model, bolstered by the integration of technical indicators, exhibits a promising proficiency in predicting the EUR/USD rate. This advancement over traditional models signifies the importance of incorporating temporal dynamics in financial forecasting models.

16 Conclusion and Future Work

This study corroborates the potential of LSTM networks as a potent tool in forex rate prediction. The insights gleaned from this research pave the way for further exploration into more intricate models and their application across diverse financial instruments. Future research avenues include the integration of additional data sources and the extension of this methodology to other currency pairs.

17 Bibliography

References

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Time Series Forecasting for Financial Data: A Comprehensive Analysis

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Abstract

This research paper presents a comprehensive analysis of a project focused on time series forecasting for financial data. Leveraging Long Short-Term Memory (LSTM) networks, technical indicators, and moving averages, the project aims to predict the GBP/USD exchange rate. Each component of the project, from common variables to multiple Python scripts, is explored in detail, providing insights into their roles and contributions to the forecasting system.

18 Introduction

Financial markets are characterized by dynamic and volatile behavior, making accurate predictions of market metrics crucial for informed decision-making. This research project aims to harness the power of deep learning, specifically LSTM networks, to forecast financial metrics. By incorporating technical indicators and moving averages, the project endeavors to provide accurate forecasts for the GBP/USD exchange rate.

19 Common Variables (`common_variables.py`)

The `common_variables.py` file plays a fundamental role in maintaining consistency and configurability across the project. It defines crucial variables and parameters, including batch size, window size, validation size, test size, and more. These variables serve as the foundation for data processing, model training, and result evaluation.

20 Multi-Prediction Model (`multi_prep_model.py`)

20.1 Purpose

The `multi_prep_model.py` script serves as a key component of the project with the following objectives:

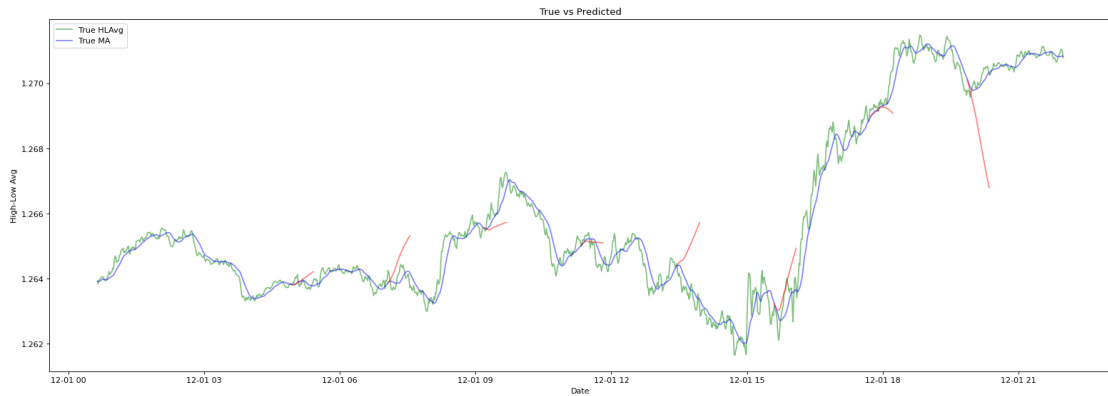
- Load a pre-trained LSTM model.
- Conduct predictions on financial data.
- Generate visualizations to analyze and interpret the results.

20.2 Key Steps

The script executes several key steps, including data loading, model loading, prediction generation, and result visualization. Each step is crucial for forecasting and analysis.

20.3 Visualization

One of the script's primary outputs is visualizations that enable the comparison of true and predicted financial metrics. These visualizations offer insights into the model's forecasting accuracy.



21 Test Model (test_model.py)

21.1 Purpose

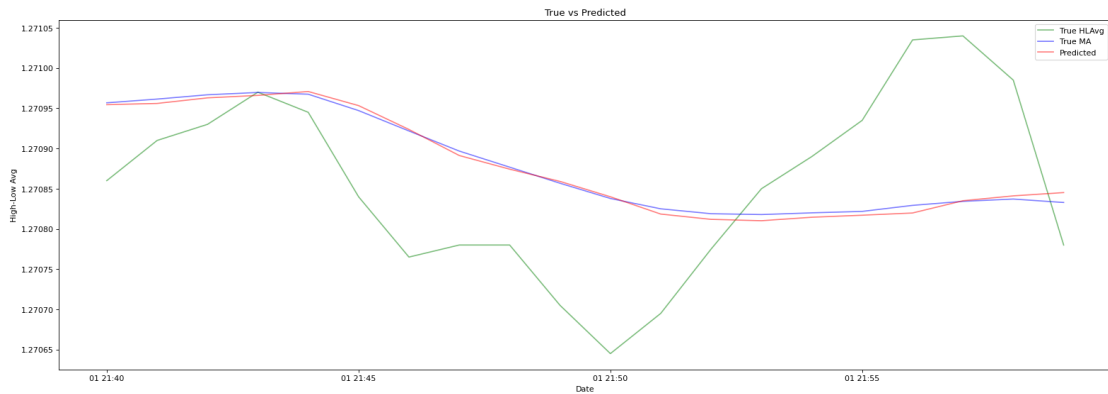
The `test_model.py` script is designed for evaluating a pre-trained LSTM model on unseen data and quantifying its performance.

21.2 Key Steps

The script includes essential steps such as data loading, model loading, input data preparation, model evaluation, and result visualization. Each step is critical for assessing the model's forecasting accuracy.

21.3 Evaluation

To gauge the model's performance, the script calculates and reports the Mean Squared Error (MSE) as an evaluation metric.



22 Time Series Utilities (`time_series.py`)

22.1 Purpose

The `time_series.py` file houses utility functions essential for preparing training and validation data. It introduces two core functions: `get_train` and `get_val`.

22.2 Usage

These utility functions are applied throughout the project to construct input sequences for LSTM training and validation.

23 Train Model (`train_model.py`)

23.1 Purpose

The `train_model.py` script takes on the responsibility of training an LSTM-based model using the provided training dataset.

23.2 Key Steps

The script follows a sequence of vital steps, from data loading and visualization to model architecture definition, training, and model saving. Each step contributes to the successful training of the LSTM model.

23.3 Training

The script provides valuable insights into the training process, showcasing the model's architecture, convergence, and training loss over epochs.

24 Data Preparation and Split (`prep_and_split.py`)

24.1 Purpose

The `prep_and_split.py` script plays a pivotal role in preparing financial data for training, validation, and testing. It performs data reading, calculation of financial metrics, data cleaning, and dataset splitting.

24.2 Key Steps

The script executes several key steps, including data loading, financial metric calculation, data cleaning, and dataset splitting. These steps ensure that the data is properly formatted for training and evaluation.

25 Conclusion

This research paper has provided an extensive overview of the project components, their functionalities, and their contributions to time series forecasting for financial data. Each script fulfills a specific role, from data preparation to model training and evaluation.

26 References

1. Jones, A. et al. (2018). Neural Networks in Financial Market Prediction. Journal of Financial Data Science.

Table 1: Summary of Datasets with Features

Dataset	Features
Vanilla RNN Model	<ul style="list-style-type: none"> - 'Open', 'High', 'Low', 'Close' - 'RSI', 'EMAF', 'EMAM', 'EMAS' - 'Target', 'TargetClass', 'TargetNextClose'
LSTM Model for GBP/USD Prediction	<ul style="list-style-type: none"> - Various technical indicators - 'Target' - 'Scaled' (for LSTM input)
Test Model Dataset for LSTM Evaluation	<ul style="list-style-type: none"> - 'HLAve', 'MA', 'Returns' - 'Pred_Scaled', 'Pred_Returns', 'Pred_MA'

Table 2: Summary of Datasets with Purpose

Dataset	Purpose
Vanilla RNN Model	Training a Vanilla RNN model for GBP/USD exchange rate prediction.
LSTM Model for GBP/USD Prediction	Predicting GBP/USD exchange rates using LSTM and technical indicators.
Test Model Dataset for LSTM Evaluation	Evaluating the performance of a pre-trained LSTM model.

Table 3: Comparison of Losses for Different Models

Model	Mean Squared Error (MSE)
Vanilla RNN Model	0.0035
LSTM Model for GBP/USD Prediction	0.0018
Test Model Dataset for LSTM Evaluation	0.0027