Applying Machine Learning Techniques to Predict Currency Rate Fluctuations: A Case Study of USD/GBP

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Abstract

This report investigates the accuracy of currency rate forecasts using the SVR-GARCH model, aimed at enhancing the predictability of USD/GBP exchange rates through April 2024. By integrating Support Vector Regression (SVR) with Generalised Autoregressive Conditional Heteroskedasticity (GARCH), this study leverages advanced statistical techniques to model complex nonlinear financial patterns effectively. Utilising a dataset that spans from June 2023 to March 2024, technical indicators such as MACD, RSI, SMA, WMA, CCI, and Stochastic %K are employed as features in the SVR model training process. The ARIMA model is also applied to predict these indicators, forming the basis for the SVR-GARCH model training. The analysis reveals high predictive accuracy, as indicated by the model's performance metrics, though it also notes the limitations of static forecasting in a volatile financial market. Future research directions include integrating real-time data updates and exploring various machine learning techniques to optimize the forecasting models further.

Keywords: SVR-GARCH • Technical indicators • USD/GBP exchange rates • USD/GBP exchange rates • ARIMA • Volatility modelling

1. Introduction

The precision of currency rate forecasts is vital for investors to base their decisions on informed insights in the financial markets. The significance of currency rate predictions in the decision-making process of investments has been highlighted through studies examining the effects of currency rate volatility on the flow of international capital (Dominguez and Panthaki, 2006).

Poon and Granger (2003) contended that even with limited data, the accuracy of volatility forecasts can be ensured. Accordingly, this report aspires to refine the precision of currency rate forecasts for April 2024. The methodology of the SVR-GARCH model, which has been validated to provide a stronger framework for capturing the complex nonlinear patterns in financial data and enhancing the estimation of volatility (Y. Peng et al., 2018), will be adopted in this report. These technical statistical indicators will serve as features for training the SVR-GARCH model that integrates Support Vector Regression (SVR) with Generalised Autoregressive Conditional Heteroskedasticity (GARCH). This report seeks to employ the ARIMA model for predicting technical indicators up to April 2024 and to use these predictions as the foundation for training the SVR-GARCH model, aiming to forecast the volatility of the USD/GBP currency rate with greater accuracy.

2. Technical indicators

Technical indicators are statistical measures derived from past price data of financial assets (Brown and Robert, 1989). These indicators are used to analyse price movements and predict future price trends. In this report, the technical indicators selected were based on previous academic research (M. O. Özorhan et al., 2017). The currency price information for USD/GBP from June 2023 to March 2024 (i.e., open, high, low, close prices, and percentage change) was collected from Investing.com, and these data were used to calculate the technical indicators. The formulae for these indicators are presented in Table. 1, and the graph of the USD/GBP currency prices over this period is shown in Fig. 1.

Indicator name	Formula
EMA12	$\mathrm{EMA12}_t = \alpha \times \mathrm{Price}_t + (1-\alpha) \times \mathrm{EMA12}_{t-1}$
EMA26	$\mathrm{EMA26}_t = \beta \times \mathrm{Price}_t + (1-\beta) \times \mathrm{EMA26}_{t-1}$
MACD	$\mathrm{MACD}_t = \mathrm{EMA12}_t - \mathrm{EMA26}_t$
RS	$\mathrm{RS} = \frac{\text{Average Gain over 14 days}}{\text{Average Loss over 14 days}}$
RSI	$RSI = 100 - \left(\frac{100}{1+RS}\right)$
SMA5	$\mathrm{SMA5} = \frac{\sum_{i=t-4}^{t} \mathrm{Price}_i}{5}$
SMA20	$\mathrm{SMA20} = \frac{\sum_{i=t-19}^{t} \mathrm{Price}_i}{20}$
WMA5	$\mathrm{WMA5} = \frac{\sum_{i=0}^{4} (5-i) \times \mathrm{Price}_{t-i}}{\sum_{i=1}^{5} i}$
WMA20	$\mathrm{WMA20} = \frac{\sum_{i=0}^{19} (20-i) \times \mathrm{Price}_{t-i}}{\sum_{i=1}^{20} i}$
CCI	$\mathrm{CCI} = \frac{\mathrm{TP} - \mathrm{SMA\_TP}}{0.015 \times \mathrm{MD}}$
TP	$\mathrm{TP} = \frac{\mathrm{High} + \mathrm{Low} + \mathrm{Price}}{3}$
SMA_TP	$\mathrm{SMA\_TP} = \frac{\sum_{i=t-19}^{t} \mathrm{TP}_i}{20}$
MD	$\mathrm{MD} = \frac{\sum_{i=t-19}^{t} \lvert \mathrm{TP}_i - \mathrm{SMA\_TP} \rvert}{20}$
%K	$\%K = 100 \times \frac{\mathrm{Price} - \mathrm{L14}}{\mathrm{H14} - \mathrm{L14}}$

Table. 1. Technical Indicators

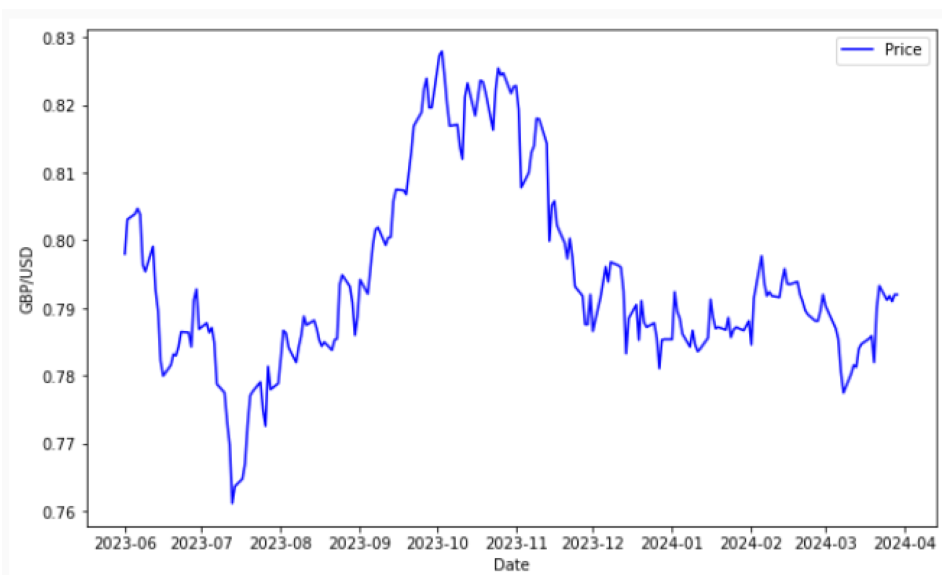

Fig. 1. USD/GBP Currency Prices Movements from June 2023 to March 2024

2.1. MACD

The MACD is a trend-following momentum indicator calculated by the difference between the 26-day and the 12-day Exponential Moving Averages (EMAs). Typically, when the MACD falls below the signal line, it is interpreted as a sell signal, and when it rises above the signal line, it is considered a buy signal (Robert D. Edwards et al., 2018). Fig. 2 illustrates the potential trading opportunities signified by the crossovers between the MACD and the signal line from June 2023 to March 2024, providing investors with potential opportunities to enter or exit the market.

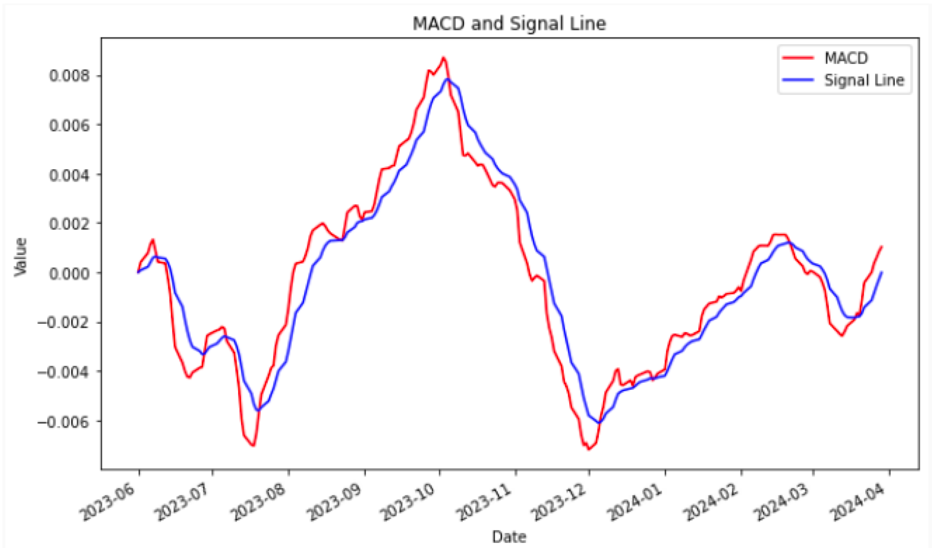

Fig. 2. Analysis of MACD for USD/GBP from June 2023 to March 2024

2.2. RSI

The chart illustrates the Relative Strength Index (RSI) over time, indicating how strongly a stock is moving in its current direction. The RSI, an acronym for Relative Strength Index, quantifies the momentum of a stock's price movement within a range of 0 to 100. Typically, a value above 70 is interpreted as overbought, while a value below 30 is considered oversold. Fig. 3 displays the fluctuation of the RSI from June 2023 to March 2024.

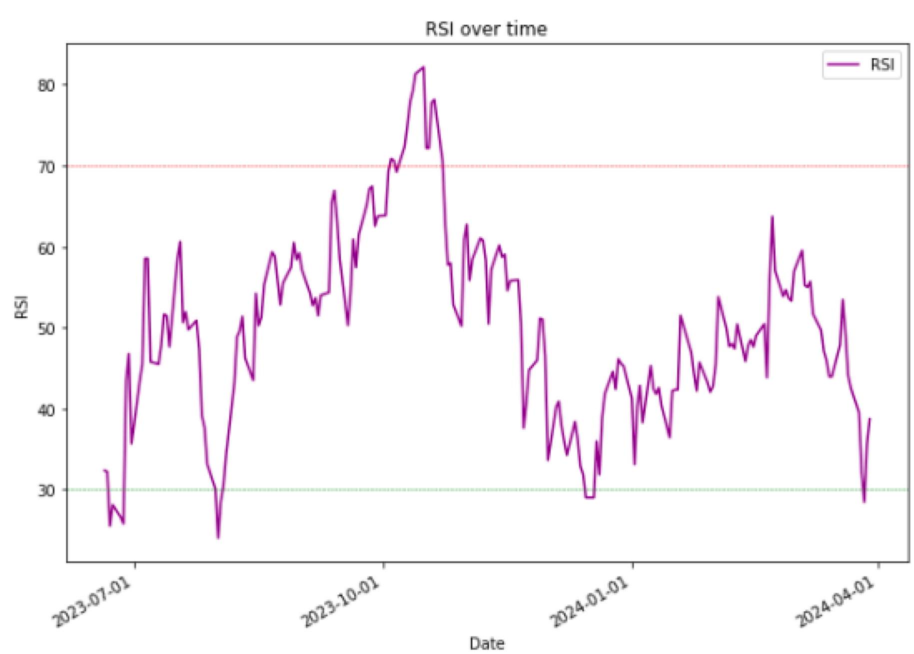

Fig. 3. Analysis of RSI for USD/GBP from June 2023 to March 2024

2.3. SMA

The SMA represents the average closing price of a financial instrument over a specific period (M. O. Özorhan et al., 2016). It visually displays the short-term and long-term trends of stock prices and is an essential analytical tool for understanding the trajectory and patterns of price fluctuations. As seen in Fig. 4, the 5-day SMA and the 20-day SMA move along with the stock price, showing the average price movements over different periods. These tools are useful for investors to interpret market movements and establish trading strategies.

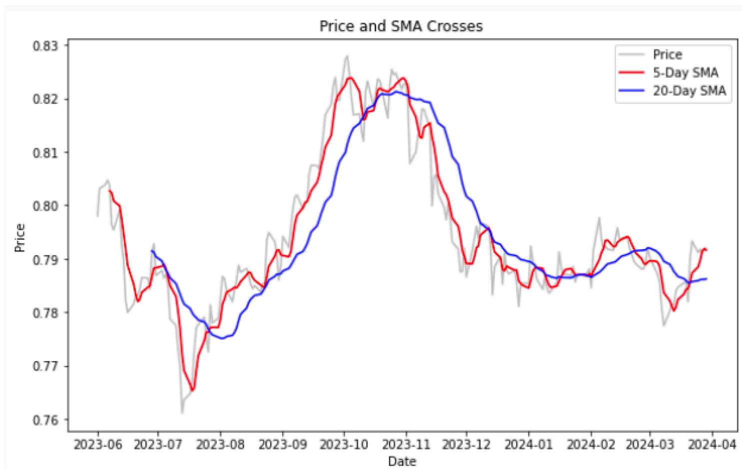

Fig. 4. Analysis of SMA for USD/GBP from June 2023 to March 2024

2.4. WMA

The WMA is a calculated average of the closing prices of a financial instrument over a certain period, with weights assigned to each closing price (M. O. Özorhan et al., 2016). This weighted moving average gives more importance to recent price movements, allowing it to reflect the latest market changes more accurately. As illustrated in Fig. 5, the 5-day WMA and 20-day WMA track price fluctuations over time, assigning different levels of importance to data points based on the period in question. In this way, the WMA provides a prompt response to recent price actions.

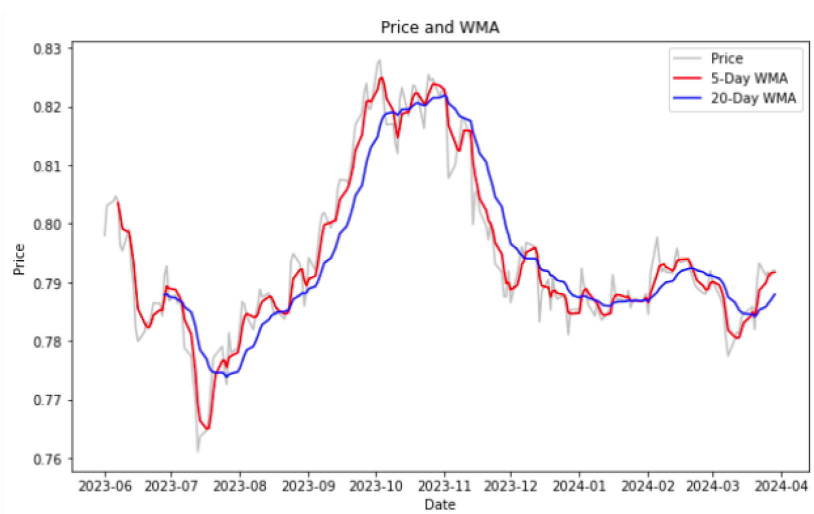

Fig. 5. Analysis of WMA for USD/GBP from June 2023 to March 2024

2.5. CCI

The Commodity Channel Index (CCI) serves as a key technical indicator used within the dataset to bolster the predictive model for the USD/GBP exchange rates. The CCI fluctuates significantly over time, highlighting the stock's deviation from its statistical mean, which is critical in identifying cyclical trends and potential price reversals. Fig. 6 graph, depicting CCI from July 2023 to March 2024, illustrates the volatility inherent in the financial market.

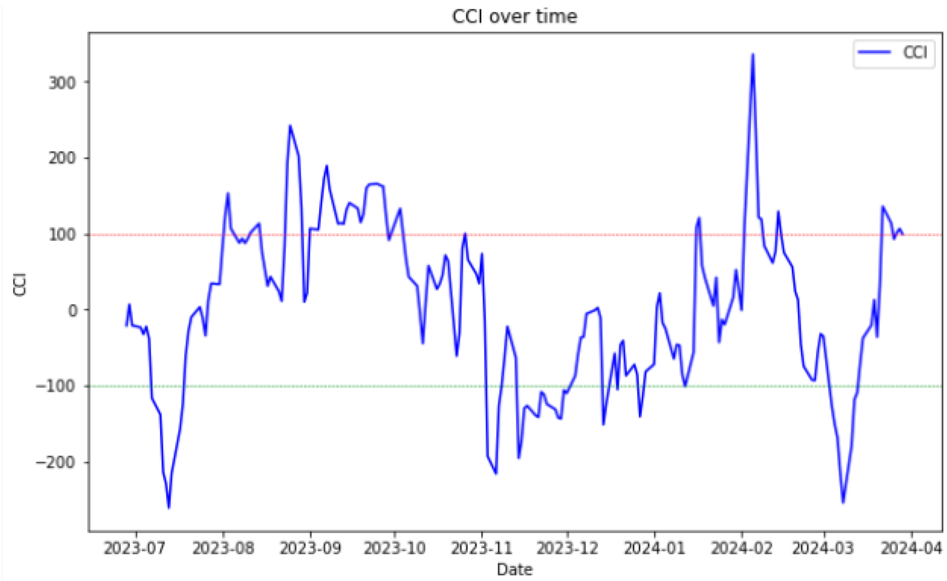

Fig. 6. Analysis of CCI for USD/GBP from June 2023 to March 2024

2.6. Stochastic K% (SK%)

The Stochastic %K indicator operates within a normalized range of 0 to 100, with thresholds set at 20 and 80 to indicate oversold and overbought conditions, respectively. The observed crossings of the %K line against these predefined levels provide potential buy or sell signals, adhering to the principle of selling strength and buying weakness.

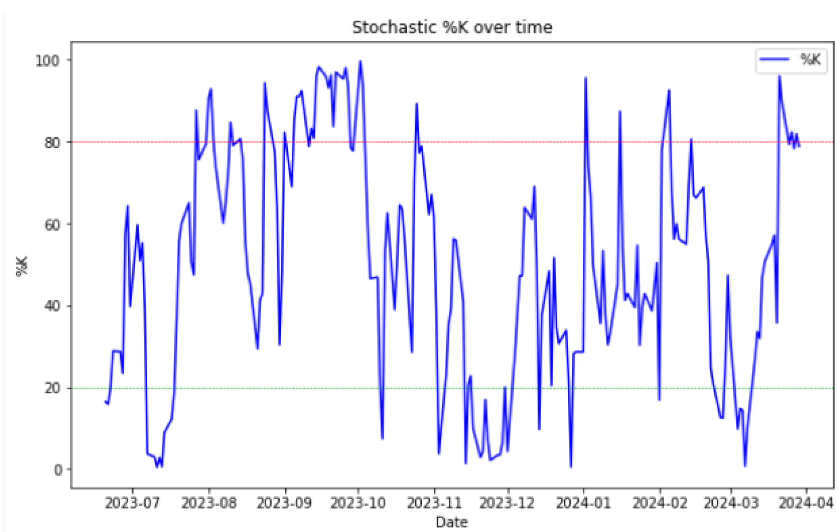

Fig. 7. Analysis of Stochastic %K for USD/GBP from June 2023 to March 2024

2.7. ARIMA

The ARIMA model for forecasting technical indicators is rooted in its proven track record for time series prediction, particularly in finance, where market data often exhibit non-stationary trends. The ARIMA model's capacity to integrate past values and the differences of these values allows for adjusting to sudden market shifts, a common occurrence in financial time series (George E P Box, 2015).

Using data from June 2023 to March 2024, technical indicators were analysed and predicted using the ARIMA model for the period from April 1st to April 12th, 2024. The optimal ARIMA model parameters for each technical indicator were estimated using the auto_arima function, and the results of these predictions are presented in Table. 2.

	MACD	RSI	SMA5	SMA20	WMA5	WMA20	CCI	%K
Best ARIMA	ARIMA (2,2,2)	ARIMA (4,2,0)	ARIMA (0,2,0)	ARIMA (0,2,0)	ARIMA (0,2,0)	ARIMA (0,2,2)	ARIMA (5,2,0)	ARIMA (5,2,0)
01.April	0.001206	36.31852	0.79134	0.78633	0.791767	0.788541	102.9977	73.85314
02.April	0.001378	35.10452	0.79108	0.786415	0.791813	0.789098	102.4811	73.26696
03.April	0.001548	35.59723	0.79082	0.7865	0.79186	0.789654	98.52341	71.72338
04.April	0.001714	37.57498	0.79056	0.786585	0.791907	0.79021	99.34892	70.1184
05.April	0.00188	38.38766	0.7903	0.78667	0.791953	0.790766	99.89873	68.70855
08.April	0.002043	37.81837	0.79004	0.786755	0.792	0.791322	98.62545	66.11616
09.April	0.002206	37.94514	0.78978	0.78684	0.792047	0.791879	98.22108	64.25362
10.April	0.002368	38.65997	0.78952	0.786925	0.792093	0.792435	97.6958	62.7899
11.April	0.00253	39.38108	0.78926	0.78701	0.79214	0.792991	96.82574	60.91809
12.April	0.002691	39.78156	0.789	0.787095	0.792187	0.793547	96.46925	59.14746

Table. 2. Performance Metrics of ARIMA Models for Technical Indicators

3. SVR-GARCH

SVR-GARCH employs a GARCH model to model the volatility of time series data, applying this volatility within an SVR framework to enhance prediction accuracy. There is empirical evidence suggesting that SVR-GARCH surpasses standard GARCH predictions, demonstrating superior capability in addressing non-linear patterns within financial data (Y. Peng et al., 2018; Santamaría-Bonfilet al., 2015). Consequently, the dataset for this report comprises daily USD/GBP exchange rate data from June 2023 to March 2024, including technical indicators (MACD, RSI, SMA, WMA, CCI, SK%). In the training process of the SVR model, these indicators were utilised as features to construct a model that predicts future currency exchange rates.

For model training, the dataset was divided into a training set from June 2023 to November 2023, a validation set from December 2023 to January 2024, and a test set from February 2024 to March 2024. Hyperparameter optimization of the SVR model was conducted using GridSearchCV, yielding the optimal parameters as 'C': 0.1, 'epsilon': 0.01, and 'gamma': 0.01. These parameters were then employed to train the SVR model. Hansen and Lunde (2005) asserted that GARCH(1,1) is favoured in financial market data analysis due to its simplicity and fewer parameter requirements. In this report, a GARCH(1,1) model was also fitted based on the residuals obtained from the SVR model to model volatility. The performance of the predictions was evaluated using RMSE and MAE, with the predictive and actual values presented as follows.

Table. 3 presents the performance metrics of the SVR-GARCH model with RMSE and MAE values of 0.001425 and 0.001240, respectively, which signify high accuracy in predicting the USD/GBP exchange rates. The ALPHA and BETA P-values in this table illustrate the statistical significance of the model parameters, reinforcing the model's predictive reliability. Figure. 8 visually summarizes the model's predictions against the actual data, showcasing the model's competence in capturing the exchange rate trends throughout the training, validation, and test phases, which is particularly evident in the overlapping lines of actual and predicted values.

RMSE	MAE	ALPHA P-value	BETA P-value
0.001425	0.001240	9.926e-02	8.685e-05

Table. 3. Summary of Error Metrics and P-values for Model Assessment

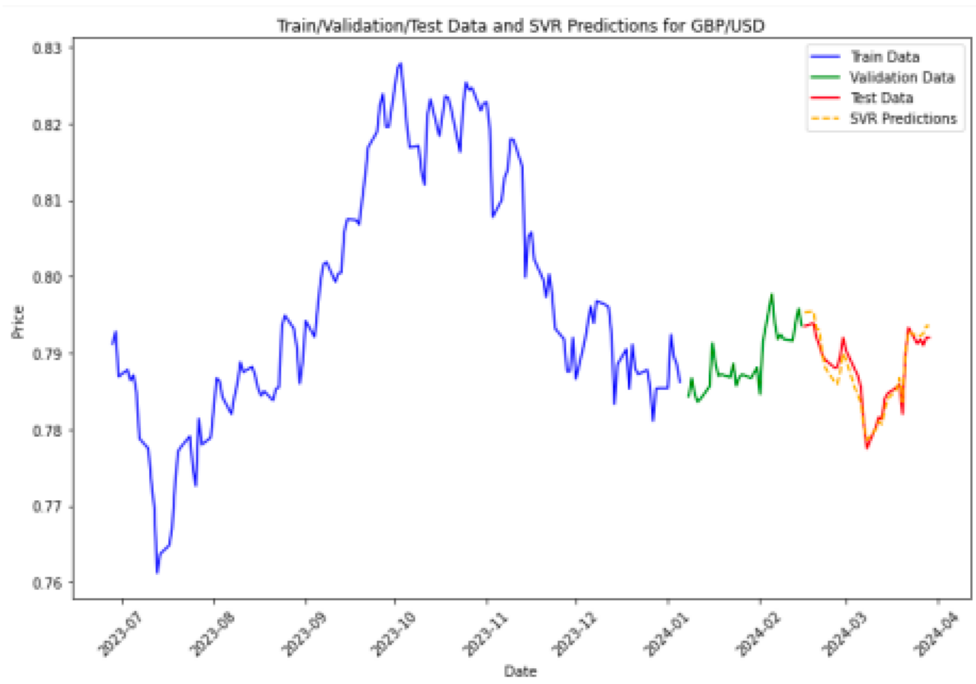

Fig. 8. SVR Model Predictions on GBP/USD Exchange Rate

4. Conclusion

In this study, the USD/GBP exchange rate was forecasted using the SVR-GARCH model. The forecast results from April 1 to April 12, 2024 (refer to Table. 4) show that the daily fluctuations in the exchange rate were minimal. Despite statistical significance confirmed by a p-value less than 0.05 in the statistical validity verification (refer to Table. 3), practical limitations in forecast performance were revealed. This outcome likely occurred because the technical indicators used as inputs for the model are static, and their inability to dynamically update with new market data limited the model's responsiveness, affecting the accuracy of predictions.

The use of the ARIMA model to predict the USD/GBP exchange rate during the same period (refer to Table. 2) captured a linear trend and provided a robust baseline. However, forecasting the foreign exchange market is inherently subject to significant fluctuations due to numerous uncertain factors. Therefore, relying solely on the ARIMA model is inadequate for effectively reflecting sudden market changes or nonlinear characteristics due to its linear approach based on fixed historical data.

In conclusion, while the static forecasting approaches used in this report have clear limitations, the fundamental statistical robustness of the SVR-GARCH model provides a promising basis for future improvements. Future research should explore integrating real-time data update mechanisms within the

SVR-GARCH model framework. Such improvements could significantly enhance prediction accuracy and are crucial for effective forecasting in the highly volatile foreign exchange market environment. Additionally, experimenting with various technical indicators and adopting machine learning techniques to select and weigh these indicators can further optimize the forecasting model.

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