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Article

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Neural networks and ARMA-GARCH models for foreign exchange risk measurement and assessment

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ABSTRACT

Market turnover levels and liquidity changes across various territories significantly influence currency prices, leading to continuous fluctuations. Consequently, traders and investors constantly seek strategies to mitigate exchange rate risks. This study aimed to measure and assess foreign exchange risk utilizing Neural Networks and ARMA-GARCH models. Data on five leading currencies, covering the period from 6 January 2016 to 28 June 2024 were sourced from the National Bank of Rwanda. Specifically, the study employed the long-short-term memory (LSTM) model, a type of recurrent neural network, to evaluate the riskiness of asset currencies. The estimated volatilities were compared with those derived from traditional ARCH-GARCH models. Notably, the LSTM model yielded lower root mean square error values compared to the ARMA-GARCH models, demonstrating superior accuracy in forecasting currency volatilities. The findings indicate that EGP and KES are riskier than USD, EUR, and GBP.

IMPACT STATEMENT

This research explores advanced methods for measuring and assessing foreign exchange risk using Neural Networks, specifically Long Short-Term Memory (LSTM), and ARMA-GARCH models. By focusing on five significant currencies traded in the Rwandan foreign exchange market, the study demonstrates the superiority of the LSTM model over traditional statistical models, offering a more accurate and reliable approach to predicting currency volatilities. These findings provide valuable insights for financial institutions, investors, and policymakers, equipping them with robust tools for risk management in currency trading and enhancing decision-making capabilities. The model's success in accurately forecasting exchange rate fluctuations also highlights the potential for integrating machine learning into finance, contributing to improved stability and foresight in volatile markets.

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1. Introduction

Typically, forex refers to the foreign exchange market in which brokerage firms and commercial banks communicate with each other on a timely basis to buy and sell currencies worldwide through Electronic Communication Networks (ECNs). This market has the largest number of financial transactions between investors and financial intermediaries, making it the largest and most lucrative financial market for future earnings worldwide. In the work of Escudero et al. (2021) and Pacelli (2012), the future earnings in terms of rate returns are predicted by both statistical models and machine learning approaches. Though the models are used, some indicators and scenarios must be considered to determine whether a currency is at risk or has high fluctuation compared to other ones. Even though many people do business locally or internationally, sometimes it is difficult for them to understand how the rate returns of currencies are calculated, fluctuated, and predicted using mathematical models.

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Since the birth of the foreign exchange market in 1970, various mathematical models have been used to forecast rate returns. Among the best models, the so-called Time series-based models have been proven to be one of the best models that study, analyze the dataset's features, and produce good results when forecasting time series values (Goodman, 1979). Moreover, the application of statistical and machine learning models to economy and business has been helpful to economists, business people, and policymakers in controlling fluctuations of currency rate returns on exchange markets (Pahlavani & Roshan, 2015). Based on Escudero et al. (2021), Mahajan et al. (2022), Classical Methods such as Autoregressive Moving Average (ARMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are extensively utilized to analyze and study the exchange rate returns of currencies. Although classic models have effectively forecasted historical time-series data, they present shortcomings when dealing with bigger data sets. In response, artificial neural networks began to be employed for financial and economic data in the 1970s. These networks use non-linear algorithms to tackle complex time series forecasting (Dautel et al., 2020). With the advancement of machine learning techniques in recent decades, Long Short-Term Memory (LSTM), a type of recurrent neural network, was developed. LSTM models sequentially train data to improve the accuracy of forecasting historical data (Van Houdt et al., 2020 and Yıldırım et al., 2021).

In technological advancement, this research sits at the intersection of finance and AI, pushing the boundaries of both fields. It contributes to the advancement of artificial intelligence (AI) technologies and their application in real-world financial scenarios, promoting innovation and technological progress. The motivation of this paper is that neural networks can leverage large datasets, including real-time market data and alternative data sources, to enhance the accuracy and reliability of risk assessments. The outcomes of this research have direct applications in the financial industry. Banks, investment firms, and corporations can implement these models to manage their FX risk more effectively, leading to better financial performance and reduced risk exposure. Neural Networks and ARMA-GARCH models are our central interest in this paper. The Long-Short-Term Memory (LSTM) model, one of the recurrent network models, will be employed to measure and assess the risks of foreign exchange currencies. The results will be compared to those produced by traditional ARMA-GARCH models, and their accuracy will be evaluated to recommend the best model for use.

The structure of this paper is as follows: Section 2 provides the literature review. The mathematical models used in this study are described in the materials and methods section, Section 3. Section 4 presents the results and discussion, followed by model evaluation in Section 5. Lastly, Section 6 contains the concluding remarks.

2. Literature review

In the fields of economy and finance, time series prediction of rate return has a long history. The volatility of the foreign exchange rate (FX) has piqued the curiosity of the media, investors, and scholars. Aliu et al., 2024 Exchange rate shocks and the reasons that cause them are at the heart of scholarly discussions and central bank policies. Frequent jumps in the FX market create uneasiness in international trade and reduce portfolio performance. The most commonly traded currency pairs in FOREX are the US dollar (USD), euro (EUR), Canadian dollar (CAD), and British pound (GBP). Due to FOREX's high trade volume, system excesses are swiftly addressed. International transactions are primarily conducted in hard currencies such as the US Dollar (USD) and Euro (EUR). The economic and geopolitical weight that the US holds worldwide made the American dollar the most reliable currency. The American dollar became the most reliable currency due to the US's economic and geopolitical weight on the global stage. The onset of the COVID-19 pandemic put global growth in negative territory and interrupted currency exchange.

Due to the precision of prediction, several researchers are more interested in forecasting rate returns using either traditional statistical models or machine learning methods. Since the turn of the 20th century, statistical models such as autoregressive moving averages and GARCH models have been applied to finance data to predict forex rate returns. According to the work of Mahajan et al., 2022, they used statistical and machine learning models to anticipate and analyze volatility in the Indian stock market. They discovered that the GARCH model has a small advantage over the LSTM model. Besides machine learning models, traditional statistics have been useful models in finance. About the work of Song et al., 1998, Tim Bollerslev 1986, Bollerslev, 2008, they employed the GARCH model to study the volatility of time series trends. They stated that the GARCH model was more dominant and perfect in determining conditional volatility in financial data to inform financial decisions (Abdalla, 2012).

Although traditional statistical models: ARMA and GARCH models have been employed to predict rate returns time series, their performance has occasionally lagged behind that of machine learning techniques. Xiong et al., 2015 and Gao et al., 2020 showed that machine learning models are better at predicting stock indexes due to their efficiency in predicting non-linear time series Xiong et al., 2015. With this development of technology and the application of data science techniques to solve real-world problems, researchers tend to use deep learning models to forecast exchange rate returns data Hiransha et al., 2018. These shifts to machine learning models demonstrate the superiority of machine learning techniques and their reliability in predicting currency rate returns. According to Aliu et al., 2024 Exchange rate stability is now carefully examined, taking into account the growing intensity of global trade and the expansion of cross-border transactions. In addition to typical economic variables, FX rates are affected by the fragility of democracies, the rule of law, and the degree of corruption.

In Rwanda, limited research has been conducted to examine and predict the rate returns of currencies in the Rwandan foreign exchange market using statistical and machine learning algorithms. Addressing this gap, our study aims to investigate and compare the accuracy of both classic statistical and machine learning models in identifying fluctuations in exchange rate returns for the British pound sterling (GBP), Euro (EUR) the official currency of twenty European Union countries, Egyptian pound (EGP), United States dollar (USD), and Kenyan shilling (KES). To achieve this, recurrent neural network-based approaches, specifically long short-term memory (LSTM), alongside the ARMA-GARCH model, were mathematically developed and tested to forecast the daily rate returns of these currencies. The forecasted values from all models were then compared with the actual values to determine which model produces the most accurate forecasts.

Neural networks have garnered significant attention in the field of foreign exchange risk measurement and assessment due to their predictive capabilities. Several studies have demonstrated the effectiveness of neural network models in forecasting foreign exchange rates (Yao & Tan, 2000). Some related work stated that for several decades, the primary focus of risk-related research has been financial market uncertainty (Segal et al., 2015). Temporal variations in financial time series characteristics are often overlooked, even though models that have undergone extensive testing and been determined to be statistically valid nevertheless have the potential to overestimate or underestimate risk. The best example of such a situation is the financial crisis of 2008. Degiannakis et al. (2012) or the more recent COVID-19-related market crash (Omar et al., 2020) as a result, the financial industry both regulators and financial institutions are turning to a better, probabilistic way of calculating risk based on historical events that are capable of quickly adapting to current shocks. Variance, particularly its shifting temporal structure or inclination to cluster, is a powerful risk driver.

Bollerslev introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which is one of many models that attempt to capture this effect. Another extension of these models is that not only the variance, but also the mean, changes with time, but the mean is usually inconsequential in terms of long-term financial returns (Fama, 1998). Financial researchers, on the other hand, are quite interested in adopting machine learning techniques. For time series data, recursive techniques such as neural networks with long short-term memory (LSTM) are ideal Goodfellow et al. (2016). Additionally, NNs provide a nonlinear estimate of the likelihood function. In GARCH models, the conditional variance function often assumes a linear or very simple nonlinear connection with the likelihood function. However, the aforementioned studies do not directly focus on the implementation of LSTM for conditional variance and this study is going to focus on that. To evaluate the performance of the models, three statistical metrics were utilized: mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE).

3. Materials and methods

3.1. Data

Among the foreign currencies available in Rwanda's foreign exchange market, five were selected for this study. Specifically, the analysis and time series forecasting of weekly exchange rate returns focused on the Kenya shilling (KES), US dollar (USD), Euro (EUR), Egyptian pound (EGP), and pound sterling (GBP). The weekly rate returns of these currencies, spanning from 1 June 2016 to 28 January 2024, were obtained from the National Bank of Rwanda (BNR), which is tasked with ensuring and maintaining price and financial stability. These currencies were chosen due to their widespread use and significant influence in Rwanda, their proportions in the Bank's

foreign exchange investment portfolio, and their role in the composition of imports. The data underwent cleaning and were divided into two sets: a training set and a testing set. These sets were utilized to train and validate the models for forecasting the exchange rate returns of the selected currencies.

3.2. Methods

The study employed the Long-Short-Term Memory (LSTM) model, a type of recurrent neural network algorithm, to analyze the volatility behaviors of exchange rate returns and to forecast exchange rate returns of selected currencies in the Rwandan exchange market. Additionally, the models were compared with ARMA-GARCH models to cross-validate the estimated volatilities.

3.2.1. Long-short-term memory model

By referring to the work of Bircanoğlu & Arıca (2018) and Chen et al. (2015), recurrent neural network algorithms such as long short-term memory are non-parametric techniques that use non-linear algorithms to train and forecast time series data. This algorithm does not require stationary data because it can perform non-stationary data due to its ability to compute complex data patterns (Dautel et al., 2020). According to the work Gao et al. (2020), LSTM is made up of four layers and numerous memory cells c_t and h_t that are always updated for each iteration t while predicting time series of forex rate return. The information flows in and out of the cell are controlled by three gates: the forget gate layer, the input gate layer, and the output gate layer. The forget gate layer is in charge of selecting which information should be saved and which should be rejected by employing an activation function where its output is in the range (0, 1). If the output is 1, all of the information is kept but when it is 0, they are dismissed. The initial step in LSTM is to decide which information to reject in the cell by using the forget gate layer equation.

$$f_t = \sigma(W_f \cdot (h_{t-1}, x_t) + b_f), \quad (1)$$

where f_t is representing the values of forget gate, σ is the activation function, x_t is the input values, W_f represents the weight, h_{t-1} is the hidden state and b_f is the bias. The second step is conducted under the input gate to determine the input values to be used in updating the memory. About Bhandari et al., (2022), the sigmoid function determines whether the input data is 0 or 1, and the hyperbolic tangent function gives weight to the provided data, determining its importance on a scale of -1 to 1 .

$$\begin{aligned} i_t &= \sigma(W_i \cdot (h_{t-1}, x_t) + b_i), \\ g_t &= \tanh(W_g \cdot (h_{t-1}, x_t) + b_g), \\ c_t &= f_t \otimes c_{t-1} + i_t \otimes g_t, \end{aligned} \quad (2)$$

where the hyperbolic tangent layer creates a new candidate value g_t . Finally, in the output gate, the hyperbolic tangent function determines which values are allowed to pass through (0, 1) and gives weight to the specified values, calculating their relevance on a scale of -1 to 1 and multiplying it with the sigmoid output (Escudero et al., 2021; Greff et al., 2017).

$$\begin{aligned} o_t &= \sigma(W_o \cdot (h_{t-1}, x_t) + b_o), \\ h_t &= o_t \otimes \tanh(c_t), \end{aligned} \quad (3)$$

where h_t is the hidden layer function, W is the vector of the weight matrix, b is the vector of bias, σ and \tanh represent the sigmoid and hyperbolic tangent functions. Furthermore, σ is a standard logistic sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$, and $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ (Sharma et al., 2020). LSTM, like other recurrent neural network algorithms, is used to forecast historical data where x_t is the input values and y_t is the output, h_t is a vector of short-term memory and c_t is a vector of long-term memory, as shown in the Figure 1.

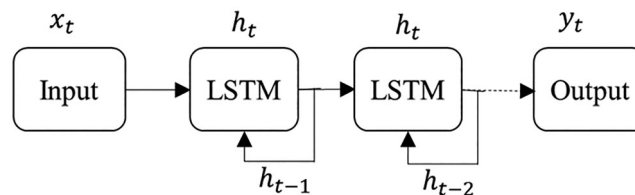


Figure 1. Algorithm for LSTM network layers (Dautel et al., 2020).

3.2.2. ARMA model

ARMA model is developed based on prior values and lagged errors and denoted as ARMA(p,q), where p represents the auto-regressive part and q represents the moving average part of the error term to be used in the prediction (Dong, 2012; Islam & Chowdhury, 2022). When a time series is stationary, the general form for the ARMA (p, q) model and its components are written as follows. AR (p) is mathematically written as:

$$y_t = c + \sum_{i=1}^p \phi_i y_{t-i} + \epsilon_t. \quad (4)$$

Whereas MA model of order q ; MA(q) is expressed as:

$$y_t = \mu + \sum_{i=0}^q \theta_i \epsilon_{t-i}, \quad (5)$$

where ϵ_t is the white noise and μ is the expectation of y_t (Siarni-Namini et al., 2018, Xiang, 2022). As previously stated, ARMA (p, q) is a combination of AR (p) and MA (q). Hence, by adding them together ARMA (p, q) is written as follows:

$$y_t = \mu + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=0}^q \theta_j \epsilon_{t-j} + \epsilon_t, \quad (6)$$

where y_t represents the daily exchange rate returns of currency, μ represents the model's intercept, ϕ_i represents the parameters of AR(p), θ_j represents the parameters of MA(q), ϵ_t represents the error terms at time t such that $t = 1, 2, \dots, n$, $E(\epsilon_t) = 0$, $\text{Var}(\epsilon_t) = \sigma^2$, and p, q are non-negative integers Ghani & Rahim, 2019. When a time series is not stationary, it becomes stationary by differencing it d -times until it becomes stable with constant mean and variance. This makes the ARMA(p, q) model become ARIMA(p, d, q) (Wong, 2014). However, if the time series is stationary, $d = 0$.

$$y_t^{(d)} = \mu + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j}. \quad (7)$$

3.2.3. GARCH model

In the evaluation of time-series data and forecasting, time-series data are subjected to generalized autoregressive conditional heteroskedasticity (GARCH) modeling (Ghani & Rahim, 2019). This model is generally an extended form of the ARCH model (Abdalla, 2012), which studies the change in variance over time. The mathematical expression of the ARCH(q) model is as follows:

$$y_t = c + \epsilon_t, \epsilon_t = z_t \sigma_t, \quad (8)$$

where y_t is the real data of time series, c is the intercept, ϵ_t is the residual, z_t is standardized residual which is i.i.d random variables with zero mean and unit variance ($z_t \sim \text{WhiteNoise}(0, 1)$). Thus, ARCH(q) model in the extended form is written as:

$$\sigma_t^2 = \eta + \sum_{j=1}^q \alpha_j \epsilon_{t-j}^2, \eta > 0, \alpha_j \geq 0, j > 0. \quad (9)$$

Sometimes, ARCH(q) occasionally fails to model time series due to large q values, resulting in a large number of estimated values. With this challenge, in 1986, (Bollerslev, 1986) worked on the extended ARCH model (Xiang, 2022), namely, the Generalized ARCH model which is mathematically expressed as follows:

$$\text{GARCH}(p, q) : \sigma_t^2 = \eta + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 + \sum_{j=1}^q \alpha_j \epsilon_{t-j}^2, \epsilon_t = z_t \sigma_t, \quad (10)$$

where η is along run volatility with conditions: $\eta > 0$, $\beta_i \geq 0, i = 1, \dots, p$, $\alpha_j \geq 0, j = 0, \dots, q$, and σ_t is the conditional standard deviation of ϵ_t given past values $\epsilon_{t-1}, \dots, \epsilon_{t-q}, \sigma_{t-1}, \dots, \sigma_{t-p}$. The GARCH

algorithm is suitable for time series data where the error term's variance is serially autocorrelated after an autoregressive moving average process. When it comes to evaluating risk and anticipated returns for assets that have clustered periods of return volatility, GARCH is a valuable tool.

4. Results and discussion

4.1. Data cleaning and descriptive analysis

The data collected was exclusively provided in the form of buying and selling prices. This data, supplied by the Central Bank of Rwanda the regulatory authority served as the benchmark for buying and selling prices. During data preparation, weekly average data was considered to capture more short-term fluctuations and trends, which are crucial for detecting early signals and making timely predictions. Consequently, the time series of rate returns was calculated using the following formula:

$$y_t = \log \left(\frac{P_t}{P_{t-1}} \right) \times 100,$$

where y_t is the daily rate returns, P_t and P_{t-1} are the absolute values of the difference of the selling price and buying price on the current day and the previous day, respectively (Abdalla, 2012). After computing each currency's weekly rate return, descriptive statistics and the augmented Dickey-Fuller test were conducted to determine whether the time series of rate returns were stationary. Table 1 provides a comprehensive overview of the descriptive statistics and measures of weekly exchange rate returns for five chosen currencies in the Rwandan exchange market. The period of analysis spans from 1 June, 2016, to 28 January 2024, and includes the currencies GBP, EUR, EGP, USD, and KES, as shown in Table 1.

Table 1 presents a detailed summary of the descriptive statistics for weekly exchange rate returns across five different currencies: GBP, EUR, KES, USD, and EGP. Firstly, the count row indicates that there are 443 observations for each currency, ensuring a consistent sample size across all currencies. The mean row reveals the average weekly return for each currency. GBP and USD show relatively higher mean returns of 0.008 and 0.012, respectively, indicating stronger average performance compared to EUR, KES, and notably EGP, which has a negative mean return of -0.025 , suggesting an average decrease in value over the observed weeks. The standard deviation reflects the volatility of these returns, with EGP having the highest standard deviation at 0.335, indicating significant variability in its weekly returns compared to the other currencies, which range from 0.010 (USD) to 0.120 (GBP). The range of returns, shown in the min and max rows, indicates that all currencies experienced considerable fluctuations. For example, EGP had the most extreme minimum return at -4.681 , indicating periods of substantial depreciation, while KES exhibited the highest maximum return of 0.837, indicating periods of significant appreciation.

The kurtosis row offers insights into the distribution's tail heaviness, with KES and particularly EGP showing very high kurtosis values of 55.929 and 132.202, respectively, suggesting heavy tails and potential for extreme values compared to the more normal distributions of GBP, EUR, and USD. Finally, the Ljung-Box statistics, which test for autocorrelation in residuals, show low values across all currencies (0.01 for most), indicating that the residuals from the models do not exhibit significant autocorrelation, suggesting that the models effectively capture temporal dependencies. In summary, these statistics reveal diverse patterns in weekly exchange rate returns across the studied currencies, encompassing

Table 1. Descriptive statistics of weekly exchange rate returns of currencies.

	GBP	EUR	KES	USD	EGP
count	443.000000	443.000000	443.000000	443.000000	443.000000
mean	0.008049	0.011934	0.006432	0.011708	-0.024546
std	0.119954	0.098825	0.069089	0.010209	0.335249
min	-0.656604	-0.366234	-0.328423	-0.019694	-4.680607
25%	-0.067389	-0.044443	-0.014249	0.006286	-0.003017
50%	0.004075	0.008242	0.001472	0.008345	0.011768
75%	0.090331	0.065422	0.017790	0.013685	0.026608
Max	0.486219	0.377659	0.837074	0.080641	0.836427
Kurtosis	2.616006	1.319654	55.928501	9.867923	132.202395
Ljung-Box	0.01	0.01	0.00	0.01	0.00

Table 2. ADF test of weekly rate returns.

Results of ADF Test	Currencies				
	GBP	EUR	EGP	USD	KES
Test Statistic	−20.980276	−22.712196	−20.980276	−2.655519	−5.194553
p-value	0.000000	0.00	0.00	0.082057	0.000009
Critical Value (1%)	−3.445232	−3.445232	−3.445232	−3.445758	−3.445867
Critical Value (5%)	−2.868101	−2.868101	−2.868101	−2.868333	−2.868381
Critical Value (10%)	−2.570265	−2.570265	−2.570265	−2.570388	−2.570414

differences in mean returns, volatility, range of fluctuations, distribution characteristics, and residual autocorrelation. These insights are essential for understanding the risk and potential return dynamics of each currency in investment or economic analysis contexts.

According to [Table 2](#), the results of the Augmented Dickey-Fuller (ADF) test conducted on weekly rate returns for five different currencies—GBP, EUR, EGP, USD, and KES—are presented. The ADF test assesses the presence of a unit root in the time series data, which would indicate non-stationarity. Beginning with GBP, EUR, and EGP, all three currencies exhibit highly significant test statistics of −20.980276, −22.712196, and −20.980276, respectively, each accompanied by p-values of 0.000000. This provides strong evidence against the presence of a unit root, suggesting that the weekly rate returns for GBP, EUR, and EGP are likely stationary, meaning their statistical properties, such as mean and variance, do not systematically change over time. Conversely, the test statistic for USD is −2.655519 with a p-value of 0.082057, which is above the commonly used significance level of 0.05. This indicates insufficient evidence to reject the null hypothesis of a unit root, implying that USD weekly rate returns may exhibit non-stationary behavior. Similarly, KES displays a highly significant test statistic of −5.194553 with a very low p-value of 0.000009, indicating strong evidence against the presence of a unit root, thus suggesting that KES weekly rate returns are likely stationary.

The critical values provided in the table assist in interpreting the significance of the test statistics. For all currencies, the test statistics are well below the critical values at the 1%, 5%, and 10% levels, further supporting the rejection of the unit root hypothesis for GBP, EUR, EGP, and KES. In contrast, USD's test statistic falls between the critical values at the 10% level but not at the more stringent 5% or 1% levels, indicating a borderline result. In summary, based on the ADF test results, the weekly rate returns for GBP, EUR, EGP, and KES are likely stationary, whereas USD returns may require further investigation due to the less conclusive p-value. These findings are crucial for understanding the long-term behavior and predictive modeling of exchange rate returns in financial analysis and economic forecasting contexts.

[Figure 2](#) illustrates the time series of exchange rate returns for the currencies considered in this study. When weekly rate returns for all currencies are converted to log returns, as shown in [Figure 2](#), there are notable fluctuations in rate returns. Specifically, high fluctuations were observed in 2020 for currencies such as GBP and KES, in 2017 for EUR and EGP, and in 2016 for USD. Additionally, various years exhibit large negative values for each currency. The trend analysis of rate returns in [Figure 2](#) demonstrates that weekly rate returns are volatile. These fluctuations result from various impacts, including COVID-19, the Ukrainian war, and social and economic effects Singirankabo et al., [2021](#)

According to [Table 2](#), the test unit roots at the p-value level for each currency are less than 0.05 (5%). Therefore, the time series of all currencies are stationary and ready to be used in the model to forecast exchange rate returns.

4.2. Fitting ARMA-GARCH models

[Table 3](#) presents the results of fitting ARMA(1,0) models to the exchange rates of five currencies: EUR, GBP, USD, KES, and EGP. Each model includes estimates for the autoregressive (AR) coefficient ϕ_1 , the moving average (MA) coefficient θ_1 where applicable, along with the associated standard errors, t-statistics, p-values, and Akaike Information Criterion (AIC) values, which indicate the goodness of fit. Starting with EUR, the AR coefficient ϕ_1 is estimated at 0.0119 with a standard error of 0.004. The t-statistic of 2.737 and a significant p-value of 0.006 suggest that the EUR exchange rate exhibits statistically significant autocorrelation, indicating that past values of the EUR exchange rate influence its current value.



Figure 2. Currency weekly rate return time series from 2016 to 2024.

Table 3. Regression results of pure AR model on currencies.

Models	Coefficients	std. Error	t-Statistic	p-Values	AIC
EUR: ARMA(1,0)	$\phi_1 : 0.0119$	0.004	2.737	0.006	-803.629
	$\theta_1 : -0.0769$	0.038	-2.012	0.044	
	$\sigma^2 : 0.0097$	0.001	18.582	0.000	
GBP: ARMA(1,0)	$\phi_1 : 0.0080$	0.006	1.326	0.185	-654.630
	$\theta_1 : 0.0004$	0.030	0.013	0.990	
	$\sigma^2 : 0.0144$	0.001	21.920	0.000	
USD: ARMA(1,0)	$\phi_1 : 0.0118$	0.002	6.818	0.000	-3347.88
	$\theta_1 : 0.7677$	0.016	49.072	0.000	
	$\sigma^2 : 4.257e-05$	1.19e-06	35.767	0.000	
KES: ARMA(1,0)	$\phi_1 : 0.0064$	0.005	1.263	0.207	-1150.65
	$\theta_1 : 0.1396$	0.026	5.372	0.000	
	$\sigma^2 : 0.0047$	7.63e-05	61.219	0.000	
EGP: ARMA(1,0)	$\phi_1 : -0.0245$	0.044	-0.553	0.580	289.505
	$\theta_1 : 0.0814$	0.033	2.494	0.013	
	$\sigma^2 : 0.1114$	0.002	47.431	0.000	

The AIC value of -803.629 indicates a relatively good fit of the model for EUR. For GBP, ϕ_1 is estimated at 0.0080 with a standard error of 0.006 . However, the t-statistic of 1.326 and a non-significant p-value of 0.185 suggest that the autocorrelation in GBP exchange rates is not statistically significant at conventional levels. The AIC value of -654.630 indicates a less optimal fit compared to EUR. In the case of USD, ϕ_1 is estimated at 0.0118 with a very low standard error of 0.002 . The high t-statistic of 6.818 and an extremely low p-value of 0.000 indicate strong statistical significance, suggesting a robust positive autocorrelation effect in USD exchange rates. The exceptionally low AIC value of -3347.88 confirms an excellent fit of the model for USD. For KES, ϕ_1 is estimated at 0.0064 with a standard error of 0.005 . The t-statistic of 1.263 and a p-value of 0.207 indicate that the autocorrelation in KES exchange rates is not statistically significant, implying that past values do not significantly predict current values. Nevertheless, the AIC value of -1150.65 suggests a reasonably good fit of the model for KES. Finally, for EGP, ϕ_1 is estimated at -0.0245 with a larger standard error of 0.044 . The t-statistic of -0.553 and a non-significant p-value of 0.580 indicate that there is no statistically significant autocorrelation effect in EGP exchange rates. The higher AIC value of 289.505 suggests a poorer fit compared to other currencies.

In summary, these results highlight varying degrees of autocorrelation in exchange rates across different currencies. Significant findings are observed in USD and EUR, suggesting that past exchange rate values strongly influence current values in these currencies. In contrast, GBP, KES, and EGP show either weak or non-significant autocorrelation effects, indicating that their exchange rates may be influenced more by other factors or exhibit more random fluctuations. The AIC values provide a quantitative measure of model fit, with lower values indicating a better fit to the data. Since all the time series are

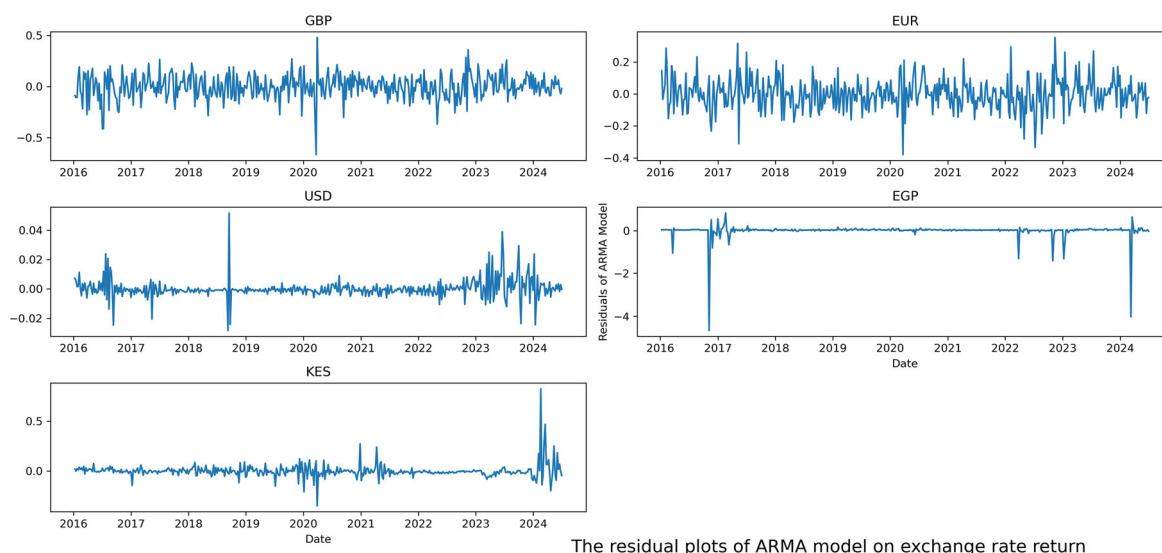


Figure 3. The residual plots of ARMA model on exchange rate returns.

stationary, the next step was to identify the optimal combination of autoregressive (AR) and moving average (MA) models to form the ARMA model. Several alternatives of AR and MA models were tested to determine the best combination for the ARMA model. The combinations with the lowest Akaike Information Criterion (AIC) values were considered the best.

To identify these optimal combinations, the `auto.arima()` function in Python was employed. This function evaluates numerous ARMA model combinations based on information criteria values such as AIC and Bayesian Information Criterion (BIC). Consequently, the model with the lowest AIC and BIC values was selected as the best ARIMA model to train the weekly rate return of currencies, the pure AR model was used as it is more stable as shown in Table 3.

The results shown in Table 3 demonstrate that while some of the estimated regression results are significant at the 95% confidence level, others are not. Following the fitting of ARMA (p, q) models to each currency, we analyzed the residuals to confirm the absence of trends and the normal distribution of the residuals. Figure 3 illustrates that the residuals display periods of reduced fluctuation interspersed with periods of heightened fluctuation, suggesting the presence of conditional heteroskedasticity in the residuals.

The residual plots for the ARMA model on the FX rate returns indicate varying model adequacies across different currencies. Specifically, the residuals for the Euro (EUR) and US Dollar (USD) are closely centered around zero with minimal variability, suggesting a good model fit. Similarly, the Great Britain Pound (GBP) also shows an adequate fit, with residuals displaying randomness and no systematic pattern. However, the Egyptian Pound (EGP) and Kenyan Shilling (KES) exhibit higher variability and volatility in their residuals, indicating potential model inadequacies. For these currencies, further investigation into model parameters or alternative modeling approaches, such as GARCH, which takes the ARMA residuals as model inputs, may be required in Table 3. Overall, while the ARMA model performs well for EUR, USD, and GBP, it may necessitate adjustments for EGP and KES to better capture the underlying data patterns in Table 4.

According to the results presented in Table 4, we can see that some of the model's coefficients are significant. The regression results of the ARIMA-GARCH model applied to different currencies reveal varying levels of significance and impact. For the British Pound (GBP), the omega parameter is statistically significant with a p -value of 0.005, indicating a small but notable effect on volatility. Additionally, the alpha parameter is significant ($p = 0.008$), suggesting that past shocks significantly influence current volatility. However, the beta parameter is not significant ($p = 0.816$), indicating no substantial effect on volatility. For the Euro (EUR), the omega parameter is not significant ($p = 0.106$), implying no significant impact on volatility. Conversely, the alpha parameter is significant ($p = 0.036$), indicating that past shocks positively and significantly affect volatility, while the beta parameter is not significant ($p = 0.266$).

Table 4. Regression results of ARIMA-GARCH model.

Volatility model					
ARIMA-GARCH model	coef	std err	t-Statistics	$p > t $	95.0% Conf. Int.
GBP	ω : 9.7119e-03	3.476e-03	2.794	5.212e-03	[2.898e-03, 1.653e-02]
	α_1 : 0.2516	9.544e-02	2.636	8.379e-03	[6.456e-02, 0.439]
	β_1 : 0.0610	0.262	0.233	0.816	[−0.453, 0.575]
EUR	ω : 4.7847e-03	2.959e-03	1.617	0.106	[−1.014e-03, 1.058e-02]
	α_1 : 0.1479	7.048e-02	2.099	3.582e-02	[9.796e-03, 0.286]
	β_1 : 0.3672	0.330	1.113	0.266	[−0.279, 1.014]
USD	ω : 8.2774e-07	1.581e-11	5.236e + 04	0.000	[8.277e-07, 8.278e-07]
	α_1 : 0.2000	0.196	1.021	0.307	[−0.184, 0.584]
	β_1 : 0.7800	0.159	4.919	8.680e-07	[0.469, 1.091]
KES	ω : 9.3791e-05	3.100e-04	0.303	0.762	[−5.137e-04, 7.013e-04]
	α_1 : 0.2000	8.159e-02	2.451	1.424e-02	[4.008e-02, 0.360]
	β_1 : 0.7800	0.195	4.009	6.094e-05	[0.399, 1.161]
EGP	ω : 0.0819	5.366e-02	1.526	0.127	[−2.331e-02, 0.187]
	α_1 : 8.9515e-03	9.821e-03	0.911	0.362	[−1.030e-02, 2.820e-02]
	β_1 : 0.2673	0.192	1.394	0.163	[−0.109, 0.643]

The US Dollar (USD) shows a highly significant omega parameter ($p = 0.000$), indicating a very small yet statistically significant effect on volatility. Although the alpha parameter is not significant ($p = 0.307$), the beta parameter is highly significant ($p = 8.68e-07$), suggesting a strong positive impact and persistent volatility clustering. For the Kenyan Shilling (KES), the omega parameter is not significant ($p = 0.762$), while the alpha parameter is significant ($p = 0.014$), indicating a significant positive effect from past shocks. The beta parameter is also highly significant ($p = 6.09e-05$), showing a strong influence on volatility persistence. Lastly, for the Egyptian Pound (EGP), none of the parameters—omega, alpha, and beta—are significant, with p -values of 0.127, 0.362, and 0.163, respectively, suggesting that the model might not effectively capture the volatility dynamics for this currency.

Overall, these results indicate that the ARIMA-GARCH model captures varying degrees of volatility dynamics across different currencies. Significant parameters highlight the impact of past shocks and persistent volatility clustering for specific currencies like GBP, EUR, USD, and KES while showing limited applicability for EGP. The ARIMA-GARCH model results for GBP, EUR, USD, KES, and EGP highlight significant volatility in GBP and USD, indicating higher risk levels. The α_1 parameter values show GBP and EUR's sensitivity to new information, while the β_1 values demonstrate long-term volatility persistence in USD and KES. These insights are crucial for investors and analysts to assess both immediate and sustained market impacts. The model's effectiveness in capturing exchange rate dynamics underscores its utility in predicting future volatility and managing risks. Overall, sophisticated statistical models are essential for accurately measuring and assessing foreign exchange risk in the Rwandan market.

The Figure 4 compares the actual rate of returns for KES, USD, EUR, GBP, and EGP against the predicted values from an ARMA-GARCH model from January 2023 to July 2024. The model captures the general trends and some volatility for most currencies, performing particularly well for USD, where predictions closely align with actual returns. However, it struggles with highly volatile currencies such as EGP, where it underestimates volatility. For KES, EUR, and GBP, the model provides reasonable predictions but occasionally misses sudden spikes or drops.

4.3. Forecasting with recurrent neural network

As previously stated in Section 3.1, the dataset of all weekly returns was divided into two sets: the training set for model training and parameter estimation, and the testing set for time series prediction Gao et al., 2020. During the training phase of the LSTM algorithm, data was scaled using activation functions such as sigmoid and hyperbolic tangent (Sharma et al., 2020, Bircanoğlu and Arıca, 2018). These functions scale the data, yielding absolute minimum and maximum values within the intervals of $[-1, 1]$ and $[0, 1]$, respectively. Let y_i represent the scaled random variable.

$$Z_i = \frac{y_i - \min(\gamma)}{\max(\gamma) - \min(\gamma)},$$

where γ is the output from sigmoid as the activation function, $\min(\gamma)$ and $\max(\gamma)$ is the minimum and maximum values of vector γ , and Z_i is a scaled value $[0,1]$. When data are scaled, LSTM is built and the

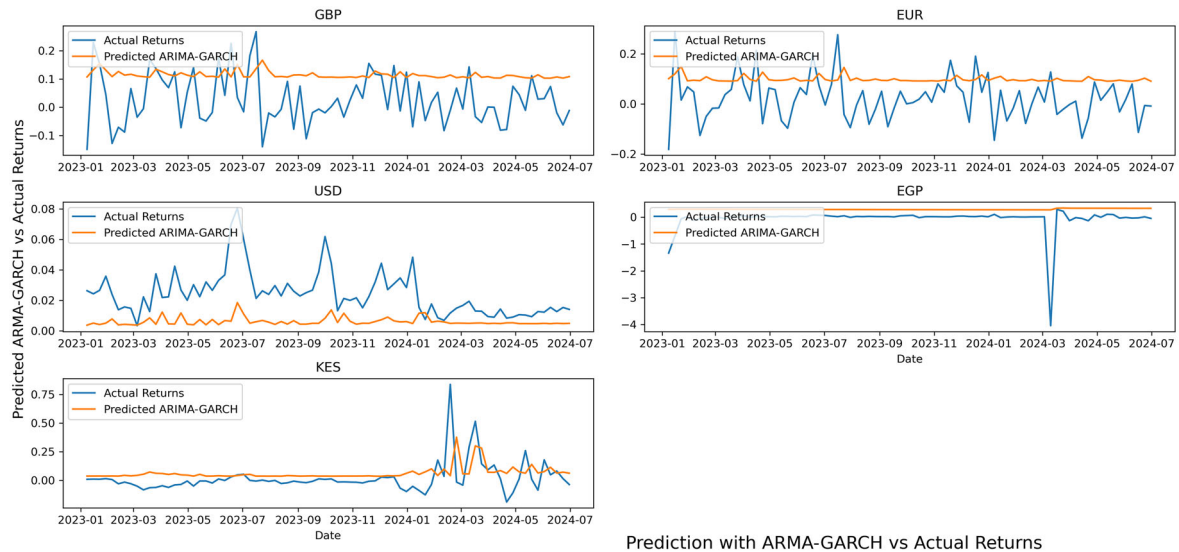


Figure 4. Prediction with ARMA-GARCH vs actual returns.

Table 5. Hyper-parameters of LSTM model.

Optimizers	Activation function	Hidden layers	epochs	batch size	Loss function
adam, gd	relu, sigmoid, tanh	(100,40,10)	5	1	mae

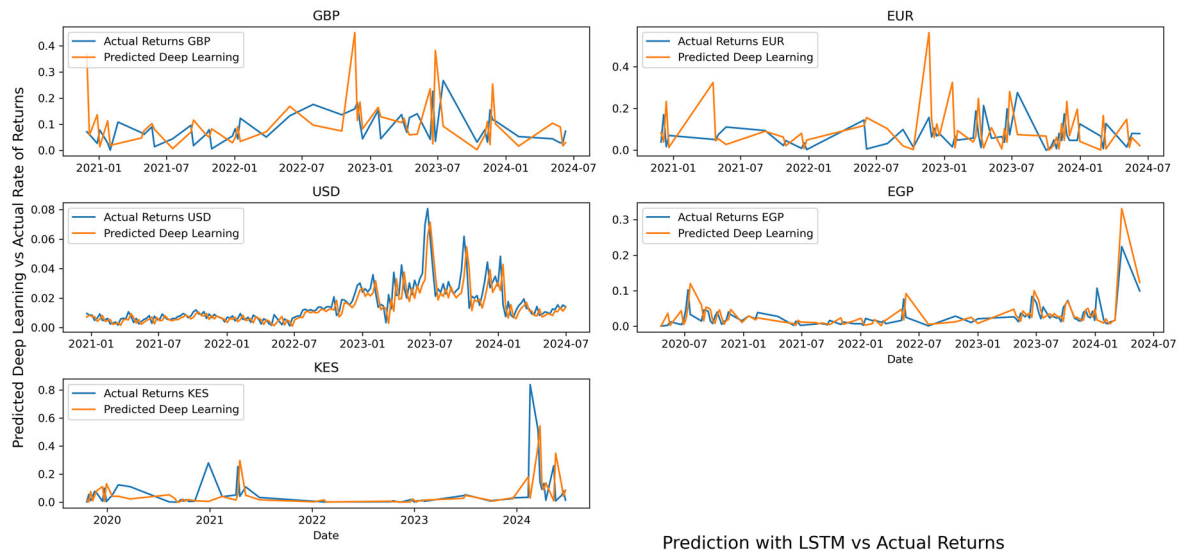


Figure 5. Prediction with LSTM vs actual returns.

activation function, loss function, number of layers, and number of neurons are updated to get the best fit of the model. Each LSTM model for predicting daily rate return was tested using different hidden layers and batch sizes, as shown in Table 5, where gd is gradient descent, tanh is tangent hyperbolic and mae is mean absolute error. As a result of model testing, with multiple testing of the unit of hidden layer, number of nodes, and epochs as the total number of iterations, the best LSTM model with the lowest loss values and the highest percentage of r-score was selected to forecast daily rate returns. In addition, during the model build-up, we tried many optimization functions to train the model however, Adam performed better than other types of optimizers, such as the gradient descent method. Adam optimized the predicted data presented in Figure 5. In terms of loss function, all of the results of the LSTM model shown in Figure 5 used mean squared error as the loss function. Based on the trials and tests made while training the model, we saw that LSTM is an iteration-based model that requires adjustments of the number of nodes, epochs, and batch size, as stated in the method development. Figure 5

Table 6. Metrics of performance for the two prediction models.

Models		MSE	RMSE	MAE
ARMA-GARCH	GBP	0.014397	0.11998	0.10592
	EUR	0.0116196	0.10779	0.09379
	EGP	0.09189	0.30314	0.2824329
	USD	0.7363	0.8581	0.64714
	KES	15.068	3.8817	3.00074
LSTM	GBP	0.0095	0.097	0.073
	EUR	0.0098	0.0991	0.0824
	EGP	0.0010	0.0567	0.0194
	USD	0.0001	0.0114	0.0081
	KES	0.0444	0.2107	0.1105

shows trend analysis of predicted values in a comparison with actual values of exchange rate returns. From Figure 5, LSTM has fitted better exchange rate returns of currencies than the ARMA-GARCH model due to its capability of fitting complex data.

According to Figure 5, the LSTM model exhibits a high level of accuracy in predicting the returns for various currency pairs, including USD/RWF, KES/RWF, EUR/RWF, GBP/RWF, and EGP/RWF. For all pairs, the model's predictions align closely with the actual returns, effectively capturing the general trends and fluctuations during the periods from January 2023 to July 2024 for USD/RWF and KES/RWF, from July 2023 to May 2024 for EUR/RWF and EGP/RWF, and from May 2023 to May 2024 for GBP/RWF. Although minor discrepancies are observed at certain points, the LSTM model accurately represents the major movements and directions of the returns. This indicates the model's robustness and effectiveness in forecasting forex returns, thereby providing valuable insights for trading and investment decisions.

5. Model evaluation

Table 6 summarizes the performance metrics of the ARMA-GARCH and LSTM prediction models, highlighting their accuracy across different currencies: GBP, EUR, EGP, USD, and KES. The metrics assessed include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). For the ARMA-GARCH model, the MSE values range from 0.0116 for EUR to 15.068 for KES. The RMSE values span from 0.10779 for EUR to 3.8817 for KES, and the MAE values range from 0.09379 for EUR to 3.00074 for KES. These results indicate that while the model performs reasonably well for currencies such as EUR and GBP, it exhibits significant prediction errors for KES. In contrast, the LSTM model demonstrates lower error rates across all metrics and currencies. Specifically, the MSE values are notably lower, ranging from 0.0001 for USD to 0.0444 for KES.

The RMSE values for the LSTM model vary between 0.0114 for USD and 0.2107 for KES, while the MAE values are relatively low, ranging from 0.0081 for USD to 0.1105 for KES. These findings suggest that the LSTM model provides superior predictive accuracy compared to the ARMA-GARCH model, especially for USD and EGP, where the error rates are minimal. Overall, the LSTM model outperforms the ARMA-GARCH model across all currencies and error metrics, demonstrating its robustness and reliability in making accurate predictions. This performance difference is particularly notable for KES, where the ARMA-GARCH model shows high errors, whereas the LSTM model maintains significantly lower error levels.

Predicted values generated by the LSTM and ARMA-GARCH models were compared to the actual values to evaluate the prediction efficacy of the models. To assess the prediction performance, statistical metrics such as MSE, RMSE, and MAE were utilized. A lower value in these metrics indicates superior model performance. As shown in Table 6, these statistical metrics were employed to compare the accuracy of the ARMA-GARCH and LSTM models in predicting rate returns.

Where

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}, \text{ and}$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |(y_i - \hat{y}_i)|.$$

In this context, y_i represents the actual values, \hat{y}_i denotes the predicted values, and n is the total number of data points. The LSTM model produced lower error values than the ARMA-GARCH model in the weekly time series, indicating that LSTM was more successful in forecasting weekly rate returns of currencies. Specifically, the error values produced by LSTM were consistently lower than those by ARMA-GARCH for weekly forecasting in the rolling forecasting model, qualifying LSTM as the best model for predicting future values of rate returns.

Based on the accuracy of LSTM, as demonstrated in Table 6, it was observed that LSTM exhibited the lowest values of root mean square errors compared to statistical models. Consequently, the LSTM model was considered the most suitable for predicting the future trend of rate returns. Future predictions, in line with the test dataset, start on -1 June- 2023 and end on 28 June 2024. Figure 5 illustrates the future behavior of rate returns and can be utilized by the general public to invest in the forex exchange of GBP, EGP, EUR, USD, and KES, which are among the currencies available in Rwanda's forex market.

6. Conclusion

This study employed statistical and machine learning models to analyze and predict the weekly rate returns of currencies (EGP, GBP, EUR, USD, and KES). Specifically, ARMA-GARCH and Long Short-Term Memory (LSTM) models are applied. Initial ARMA model fitting revealed heteroskedasticity in the residuals, which prompted the use of the GARCH model to capture the volatility of the time series. To improve the forecast accuracy, The ARMA and GARCH models were combined as ARMA-GARCH, capturing both the temporal patterns and volatility structure of the data.

As illustrated in Table 3, the ARMA model provided key insights into the coefficients and their significance for each currency. However, Table 4 demonstrated that the ARMA-GARCH model offered a more comprehensive understanding of time series volatility. Despite this, the LSTM model outperformed both, yielding the most accurate forecasts when compared to actual weekly rate returns. As highlighted in Table 6, LSTM excelled in minimizing loss, surpassing the classical ARMA-GARCH model. Additionally, Figure 4 further visualizes the comparison between actual and predicted returns using the ARMA-GARCH model. Moreover, Figure 4 revealed that the ARMA-GARCH model struggled to capture volatility spikes, particularly for GBP, EUR, and USD, where predictions appeared smoother than actual returns. Likewise, USD predictions missed significant peaks, and EGP and KES displayed trends that did not reflect sharp movements.

These findings have practical implications for guiding future research and assisting investors in understanding rate return fluctuations. The study recommends exploring alternative machine learning models, such as the multilayer perceptron (MLP) and hybrid models like CNN-LSTM, to improve accuracy in forecasting volatile markets.

Author' contributions

We are submitting our manuscript entitled 'Neural Networks and ARMA-GARCH Models for Foreign Exchange Risk Measurement and Assessment' for consideration for publication in Cogent Economics and Finance (Open Research).

As the corresponding author, I would like to provide the author contributions statement for this manuscript:

1. Elysee Nsengiyumva contributed to Writing - Original Draft Preparation, conception and design, analysis and interpretation of the data, Visualization, and revising it critically for intellectual content, and the final approval of the version to be published.
2. Joseph K. Mung'atu contributed to the Writing - Review, Supervision, Editing of the manuscript, and the final approval of the version to be published.
3. Idrissa Kayijuka contributed to the Writing - Review, Editing of the manuscript, and the final approval of the version to be published.
4. Charles Ruranga contributed to the Writing - Review, Supervision, Editing of the manuscript, and the final approval of the version to be published.

We confirm that all authors have reviewed and agree with the content of this letter and the author's contributions statement.

Thank you for considering our manuscript for publication in Cogent Economics and Finance (Open Research). We look forward to hearing from you soon.

Sincerely,

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Data availability statement

Data used was availed by the National Bank of Rwanda (BNR) and may be accessed upon reasonable request from the corresponding author.

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