VFAST Transactions on Software Engineering
https://vfast.org/journals/index.php/VTSE@ 2025, ISSN(e): 2309-3978, ISSN(p): 2411-6246
Volume 13, Number 4, October-December 2025 pp:36-52

Comparative Analysis of Exchange Rate Forecasting Techniques: Emphasis on Machine Learning Algorithms for Pakistan

Urva Zainab[1], **Attra Ali**[2], **Kifayat Ullah**[2*], **Emal Hanafi**[3], **Palwasha Seher**[4]

[1]PIDE School of Economics, Pakistan Institute of Development Economics, Islamabad, Pakistan; [2]Institute of Business Management, Karachi, Pakistan; [3]School of Economics and Management Science, University of Science and Technology Beijing, China; [4]Department of Physics, The Women University Multan, Pakistan

Keywords: *ARIMA, Artificial Neural Network, Double Exponential Smoothing, Exchange Rate, Forecasting, Machine Learning, Mean Absolute Percentage Error, Mean-Absolute Error, Mean-Squared Error, MLP, Time Series.*

Journal Info:
Submitted:
July 03, 2025
Accepted:
October 31, 2025
Published:
November 12, 2025

Abstract

The exchange rate is crucial because it can influence a country's economy. It helps brokers and traders in operational decisions that help reduce risk and maximize profits. Many methods of forecasting currency exchange rates exist. The present study focused on different methodologies, including Box-Jenkins, Holt's practice, artificial neural networks, Facebook Prophet Model, and Multilayer Perceptron (MLP) for predicting exchange rates. The performance of these techniques is evaluated based on small mean squared error, mean absolute error, and mean absolute percentage error. The results revealed that MLP outperformed all the models. It is a promising method to forecast the exchange rate of Pakistan because it gives a minor forecast error. In addition, the predicted values using MLP are very close to the actual values. The experimental results and time series plot revealed that the exchange rate of Pakistan will slightly increase in the upcoming months. It is concluded that the present study will help to determine the aggregate demand for domestic currency in the coming months. It is also helpful for the government and policymakers. However, understanding exchange rates is essential for anyone involved in international business and finance.

***Correspondence author email address:** kifayat932@gmail.com
DOI: 10.21015/vtse.v13i4.2183

1 Introduction

The word exchange rate can be explained using economic phenomena such as trade imbalance, price dynamics, trade flow, and current account balances. The importance of the exchange rate has been discussed broadly in the literature due to its significant role in promoting economic growth and promoting international acceptance, as discussed by [32]. The exchange rate is an essential term that plays a vital role in determining a country's external position. The real exchange rates have a positive effect on the traded commodities and may aid in the economic growth. The currency of a nation is very important in dictating the economic well being since it influences the aspects of trade, investment and domestic production. Moreover, better economic growth and domestic production are some of the important factors in ascertaining the overall prosperity of a country. The growth in production means that the anticipated revenues have been achieved. In addition, the increase in revenue triggers the demand of the local currency. But with the rise in imports, there is the rising demand of foreign exchange which causes a depreciation in the worth of the local currency. The foreign currency demand is also increased by the increase in imports which causes depreciation of the local currency. On the other hand, stability in exchange rate results in increased foreign investment, increased exports, and improved changes in the balance of trade in the country. The exchange rate of any country is used as a reference point to determine the economic position of the country in the global market, and also to strengthen the internal economic stability of the nation. With a stable exchange rate, an environment that supports increased foreign investment is also maintained. Besides, it can also increase the rate of exports and cause the country to have a better balance of trade. For more details, see [9, 22, 43, 53] and the reference cited therein.

The value of a certain currency in relation to the other currencies in the foreign exchange market is called the devaluation and appreciation. Depreciation is described as a fall in the worth of a currency as compared to other currencies. Appreciation however is an appreciation of the value of a currency compared to other currencies. Depreciation may be a result of inflation, economic depression, reduction in export demand or speculation in the market. Appreciation can occur due to factors such as economic growth, increased demand for exports, higher interest rates, or market confidence, see [15, 28].

The change in the trend of the exchange rate has negative impacts on the trade deficit of a country causing inflation and reduction in investment. Increase in inflation decreases the competitiveness of the country in the international market and therefore low exportation and demand of the local currency. As a measure to curb the adverse effects of exchange rate instability, one possibility is to give more consideration to trade with the developing nations and trade mutually in their respective currencies as opposed to being overly reliant on foreign currencies. To get more insights and fully know the information, one may refer to the works of [9, 16, 48] and the references in them. The domestic prices can have been affected through the regulation of the national money and trying to stimulate the domestic economy, Exchange rate is an important factor that determines the balance of trade of a country, exports, and imports[47]. The exchange rate plays a significant role in shaping a country's trade balance, as well as its exports and imports. To gain a deeper understanding of how fluctuations in the exchange rate impact export and import dynamics, it is recommended to refer to the works of [8, 19, 23, 34, 36, 49, 62–65] for further insights and detailed information.

Moreover, in this analysis, we operate the Facebook Prophet model that is open-source time series forecasting, which processes trends, seasonality, holidays, and missing data. It uses a Bayesian framework to model these components automatically, making it user-friendly for both experts and non-experts. Similar to models like MLP (Multi-Layer Perceptron), NNAR (Neural Network Autoregression), Holt Exponential, and Auto-Regressive Integrated Moving Average (ARIMA), Prophet can be used for forecasting by identifying patterns in historical data. However, Prophet stands out by its flexibility to incorporate seasonal effects and holidays directly into the model, making it highly effective for real-world data with complex seasonal variations. Like these traditional methods, Prophet can be used for long-term predictions and adjusted to account for different trends and cycles in the data. [57] studied, the trade-off between risk-return was investigated within the framework of CAPM and its validity was tested on the daily returns of companies listed in the chemical, textile and food sectors of the Pakistan stock market during the period July 2004- Feb 2014. Additionally, [40] applied ARIMA and machine learning models to forecast exchange rates in Pakistan, but their analysis was based on data starting from 2019. In contrast, our study utilizes a more comprehensive dataset, spanning from 1970 to July 2025. Furthermore, we employ robust algorithms, such as the Facebook Prophet model. Similarly, [1, 46] utilized both classical and machine learning models for exchange rate forecasting; however, our models demonstrate superior performance, yielding the lowest forecast errors, as presented in Table 2.

The current study is being conducted to forecast Pakistan's national currency exchange rate using various methodologies such as Box-Jenkins, Holt's method, ANN, and MLP. However, research has revealed conflicting views on the relative performance and superiority of ARIMA, DES, and ANNs models to time series prediction, particularly for different data sets [41]. This paper aims to clarify the divergent views in the literature concerning whether ANN with MLP is superior to ARIMA and Double ES methods for accurately predicting national currency exchange rates. The objective of this study is to forecast the currency exchange rate of Pakistan. However, if it is predicted to rise in the coming years, policymakers and the government can implement various measures to address the situation. It is important to note that the specific actions taken by policymakers and the government would depend on the prevailing economic conditions, policy objectives, and available policy tools.

The remainder of the paper is organized as follows. Section 2 contains a review of the literature on Box-Jenkins, Double Exponential Smoothing (DES), ANN, and MLP models. This is followed by the development of the presented methodology to forecast exchange rates in Section 3, and the empirical analysis and discussion using the Stock Exchange rates in Section 4. Section 5 compare the classical and machine learning models in terms of MSE, MAE, and MAPE and discuss the limitation of the study. Finally, Section 6 concludes the study by summarizing the main findings including future works.

2 Literature Review

Numerous researchers have proposed various techniques for forecasting time series data. A concise review of the literature pertaining to three prominent methodologies, namely, the Box-Jenkins approach, DES, ANN, and the Facebook Prophet model, is presented in this section.

Using ARIMA, [37] created a forecasting framework. They looked at the conventional Box-Jenkins method, which can be rather subjective, and the objective penalty function criterion as two methods for detecting ARIMA models. [14] reviewed the previous 25 years of time series forecasting research and concluded that a good forecasting method is one that predicts accurate and timely data. If a forecast can be obtained accurately and on time, it will result in a more accurate prediction. So, in order to get a better prediction, you must first select a good forecast. [18] concentrated on demand characteristics. ARIMA models are used to forecast the short and long-run price and income elasticities of Turkey's sectoral natural gas demand. [26] used ARMA methodology and GARCH family models to forecast rice yields in four Pakistani provinces from 1947 to 2009. [7] investigated the forecasting of food crop production and yield in Pakistan. The ARIMA model is used to forecast wheat, rice, and maize production from 2012 to 2030.

The DES approach, which Holt first suggested in 1957 for the level and trend estimate procedure, is another helpful technique for forecasting time series data. When data demonstrates a trend, [27] looked into the use of the DES approach. Two components—level and trend—must be adjusted in this approach, which is comparable to basic smoothing in that regard. [55] compared the AI Model's predicting performance against those of two straightforward models, the DES and Double Moving Average. By determining the average price of sugar in seven traditional marketplaces in Depok from 2014 to 2016, [20] compared the DES and ANN techniques. The ANN technique was shown to be better suitable for predicting the typical price of sugar in Depok. [45] forecasted short-term aviation passenger volume using DES models. [24] used the DES and Box-Jenkins techniques to forecast cement output in Sudan.

Additionally, there are other alternative methods to time series forecasting; ANN is one of them and has been actively researched and applied in this field. There are no requirements in ANNs, to provide a particular model shape. When there is no theoretical direction to propose an acceptable data generating procedure, this strategy is applicable for many empirical data sets. [54] found that the ANN model beat the conventional ARIMA models when comparing the stock forecasting ability of ANN and ARIMA models. Similar to this, [25] examined the performance of ANNs and ARIMA in forecasting time series, coming to the conclusion that ANNs performed better than ARIMA in predicting the direction of stock movement since the latter could find hidden patterns in the data utilised. Highest ozone concentration predicting abilities of the ARIMA and ANN and models in daily basis were also contrasted by [39].

According to the empirical findings, the ANN model outperformed the ARIMA model [3, 4]. A hybrid model proposed by [56], which combines both ARIMA and ANN models that take use of each model's unique advantages in both linear and nonlinear modeling. The outcomes demonstrate that in terms of predicting accuracy, the combined model beats any of the separate models. In predicting the Korean Stock Price Index, [33] evaluated the effectiveness of ARIMA and ANN models. According to [6], the computational strengths of numerous artificial intelligent schemes have been demonstrated to be a tool in providing new and effective ways of dealing with a variety of existing and emerging challenges. Some of the recent studies on time series forecasting using machine learning algorithms can be found in the work of [61, 66–69].

The Facebook Prophet model is a widely-used open-source forecasting tool designed to handle time series data with strong seasonal patterns and multiple seasonality. Developed by Facebook's Core Data Science team, Prophet is known for its simplicity, scalability, and ability to accommodate missing data, outliers, and holidays. Unlike traditional time series models, Prophet automatically detects and adjusts for daily, weekly, and yearly seasonality, making it particularly suitable for business applications where such patterns are common. Research has shown that Prophet's performance rivals more complex models like ARIMA and Gaussian Processes, particularly in real-world, noisy datasets [50]. Its flexibility and ease of use have led to its adoption in fields ranging from sales forecasting to capacity planning, enabling both data scientists and non-experts to implement robust forecasting solutions [38].

3 Data and Methodology

This paper analyzes and forecasts the time series data using Box-Jenkins Methodology, and Machine learning models/algorithms.Thw flow of methodology is shown in figure 1.

Data

In this study, we have used data related to the exchange rate of Pakistan and forecasted it for the next five years. The dataset is sourced from the Food and Agriculture Organization (FAOSTAT) and is available at https://www.fao.org/faostat/en/#data/PE. The dataset spans from 1970 to 2025 and contains monthly data, with 698 observations from January 1970 to July 2025. We specifically used data for the exchange rate from the local currency unit (PKR) per US Dollar (USD). The dataset includes a variety of information such as domain code, currency unit, area code, element code, year code, element, month, month code, and value. For each year, starting from January to December, the dataset provides the average monthly exchange rate for each month, as well as an additional value representing the average exchange rate for the entire year. For the period from January 2025 to July 2025, we obtained data from https://www.exchangerates.org.uk/USD-PKR-spot-exchange-rates-history-2025.html, as FAOSTAT did not provide data beyond December 2024. The additional data were included to extend the series and enable short-term forecasting. Both FAOSTAT and exchangerates.org.uk are reliable sources, and the exchange rate values from both are consistent in magnitude and trend, ensuring data compatibility.

The ARIMA Methodology

Several predictive models have been developed in literature to estimate future values; the Box-Jenkins methodology is one of them, which was developed in 1976. This method depends on autoregressive,

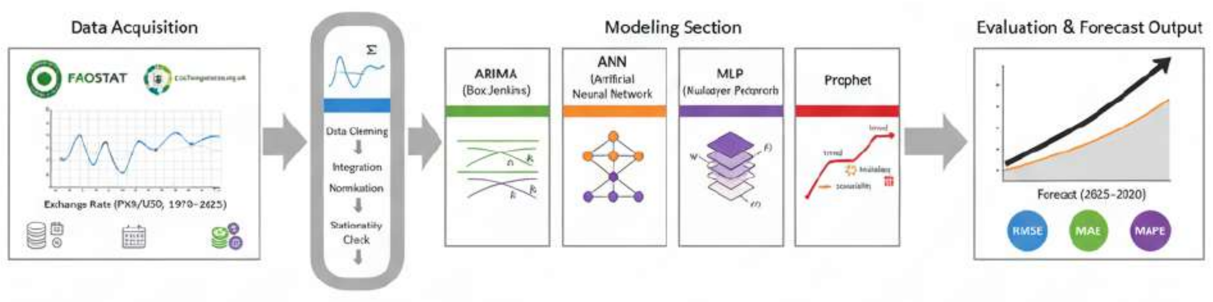

Figure 1. Methodology workflow for exchange rate forecasting using statistical and machine learning models (1970–2030)

integrated (difference), and moving average models. In this methodology, non-stationary data can only be used once stationarity is achieved. After estimating the parameters of the model, diagnostic checks should be made. If the model is appropriate by diagnostic checking, forecasts are made; alternative models should be considered [12].

A process X_t is said to follow an ARIMA(p, d, q) model if:

$$\Phi(B)(1-B)^d X_t = \theta(B)Z_t, \tag{1}$$

where ϕ and θ are the AR(p) and MA(q) parameters, respectively. The residuals, denoted as Z_t, are independently and identically normally distributed (i.i.d.) as $N(0, \sigma^2)$.

Holt Exponential Smoothing

One of the effective approaches to data analysis and forecasting of time series data is the Holt Exponential which is best applicable to data with clear trend with no seasonality trends. This model is a variant of simple exponential smoothing (ETS) and it is composed of two parts; a level, which gives the current value and trend which gives the rate of change of the value with time. The Holt approach gives a superior forecasting because it comprehends either the increasing or the decreasing trend of the data over a period of time and can be readily carried out in statistical analysis program like R, where modeling work and drawing of forecast plot can be done. Holt's double ETS method, or DES, is another predicting technique. It extends the simple ES to forecast trend component-based time series data. This technique is applicable whereby the series of times has a trend factor. Holt' involved in this method: smoothing constant for level ($0 < \alpha < 1$) and for trend ($0 < \beta < 1$). The three equations used in Holt's method are: The exponentially smoothed series, or current level estimate:

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{2}$$

The trend estimte

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{3}$$

The forecast for p periods into the future

$$\widehat{Y}_{t+p} = L_t + pT_t \tag{4}$$

where, L_t is the new smoothed level value, T_t is the trend estimate, p is the number of periods to be forecast into the future, and $\widehat{Y}_{t+p}$ is the forecast for p periods ahead. In this study, we utilized $\beta = 0.9$, which was determined after optimizing the β values to minimize the MSE of the HE method.

Artificial Neural Network

ANN, also known as a neural network, has made significant progress. ANN can handle several problems in a scientific discipline. In many fields, the most precise and popular forecasting models, including engineering, finance, social, business, economic, and foreign exchange rates, are ANNs as a soft computing method see [30, 31] and the references cited therein for more details. Its distinctive qualities draw scholars and industry practitioners interested in forecasting time series data. In this technique, three layers are used, one is the input layer, which is of data entry; the other one is the processing of data which takes place in the middle layer; and the third layer is the output layer which provides results, see [21] for more detail. The mathematical form of ANN is given by:

$$y_j = f\left(\sum_k w_{jk} x_k + b_j\right), \tag{5}$$

where y_j is the output variable, x_k denotes the input from the k^{th} node in the j^{th} layer, w_{jk} is the weight of the link between node k and the nodes in the previous layer, and b_j is the bias to the node. This weighted sum is passed along to an activation function $f(\cdot)$ to produce the output of the node. The sigmoidal function is the most commonly used activation function, defined as:

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{6}$$

Multilayer Perceptron

A MLP is a type of artificial neural network that consists of multiple layers of interconnected nodes (neurons). It is one of the most widely used and well-known architectures in deep learning. MLPs are primarily used for supervised learning tasks such as classification and regression. The MLP consists of an input layer, one or more hidden layers, and an output layer. The key advantage of MLPs lies in their ability to learn complex non-linear relationships between input and output data. They are capable of capturing intricate patterns and features from the input data, making them well-suited for tasks such as image recognition, natural language processing, and time series analysis. Mathematically, the signal processing of the MLP model is given by:

$$h_j^{(l)} = f\left(\sum_{k=1}^{n^{(l-1)}} w_{jk}^{(l)} h_k^{(l-1)} + b_j^{(l)}\right), \quad l = 1, 2, \ldots, L, \tag{7}$$

where, $h_j^{(l)}$ is the output of the j^{th} neuron in the l^{th} layer, $h_k^{(0)} = x_k$ are the input features, $w_{jk}^{(l)}$ is the weight of the connection between the k^{th} neuron in layer $(l-1)$ and the j^{th} neuron in layer l, $b_j^{(l)}$ is the bias term for the j^{th} neuron in layer l, $f(\cdot)$ is the activation function (e.g., sigmoid, ReLU, tanh). Finally, the output layer produces the prediction as:

$$y = g\left(\sum_{k=1}^{n^{(L)}} w_k^{(L+1)} h_k^{(L)} + b^{(L+1)}\right), \tag{8}$$

where $g(\cdot)$ is the activation function of the output layer, chosen according to the learning task (e.g., softmax for classification, identity for regression).

The Facebook Prophet Model

The Data Science Team at Facebook created Prophet in 2017, [52]. Strong seasonal effects in time series and several seasons of historical data are ideal for its effectiveness. Prophet usually handles outliers well and is resilient to missing data and trend changes. The model's general concept is comparable to that of a generalized additive model. It makes use of a decomposable time series model [13] that has three primary model components, which are the holidays, seasonality, and trend.

$$Y_t = g_t + s_t + h_t + \epsilon_t, \tag{9}$$

where ϵ_t denotes unconditional changes unique to a business, an individual, or a situation, h_t denotes the impacts of holidays on the prediction, s_t denotes seasonality (periodic or short-term changes), and g_t denotes trends (changes over a long period of time). The forecast is Y_t and it is also known as the error term. Prophet is attempting to fit several linear and nonlinear functions of time as components by using time as a regressor.

The selection of forecasting models in this study was driven by the specific characteristics of the data and the strengths of each model. ARIMA was chosen due to its proven effectiveness in modeling temporal dependencies in univariate time series data without seasonal effects. For example, [17, 40] demonstrated the success of ARIMA in forecasting financial time series data, which exhibit strong autocorrelation but no significant seasonal patterns. Holt's Exponential Smoothing was included for its ability to capture linear trends in data without seasonality, making it suitable for datasets with trends but no seasonal fluctuations, as shown in studies like [35], where it was effectively applied to sales forecasting in retail data. ANN and MLP models were selected because of their ability to capture complex, non-linear relationships in high-dimensional data. For instance, [5] used MLP to forecast energy consumption in Iran, showing the model's ability to learn intricate patterns from large datasets with multiple influencing factors. Similarly, [10] used the ANN and MLP models and forecast the six days ahead of COVID cased in Brazil. Finally, Prophet was chosen for its robustness in handling time series data with strong seasonal patterns and holidays. A study by [51] demonstrated the effectiveness of Prophet in forecasting web traffic, which is influenced by both seasonal trends and special events like promotions. These models were selected over others based on their individual strengths and the nature of the data, allowing for a comprehensive comparison of both classical and modern forecasting techniques.

4 Results and Discussion

In this section, various time series model including [11], ANN and DES model/algorithms are used to forecast the exchange rate of Pakistan.

4.1 Data Preprocessing

Before applying the time series and machine learning models, data preprocessing was performed to ensure accuracy and consistency. Since the dataset was already in time series form, only minimal adjustments were required. Missing values were treated using linear interpolation, and outliers were examined and corrected where necessary. For machine learning models (NNAR and MLP), the data were normalized between 0 and 1 to enhance training stability. Stationarity was verified using the ADF test, and differencing was applied where needed for ARIMA models to ensure reliable estimation.

4.2 Box-Jenkins Methodology

For finding, choosing, and evaluating conditional mean models for discrete univariate time series data, [11] provided a five-step technique which is given below.

Figure 2 demonstrates the time series plot of the exchange rate in Pakistan at a level and second difference, respectively. Firstly, the plot at a level indicates an upward trend that depicts that data is not stationary. Therefore, to eliminate the trend and to make the series stationary, difference at lag two is taken. Meanwhile, after applying difference, the plot suggests that data is stationary, as shown in Figure 3.

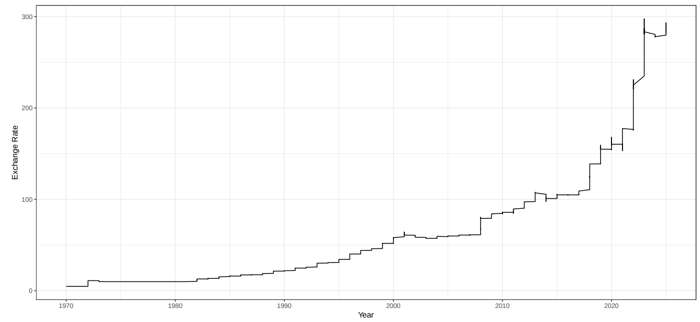

Figure 2. Data plot of exchange rate from January 1970 to July 2025

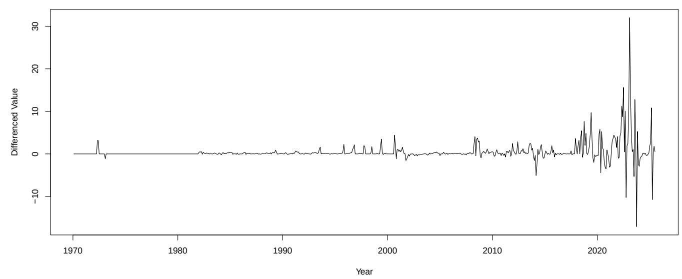

Figure 3. Stationary Plot after first Difference

Unit Root Test

The stationarity of the data was evaluated using the enhanced Augmented Dickey-Fuller (ADF) test. The null hypothesis in the ADF test can be defined as the series is not stationary, while in the alternative viewthe series is stationary. The significance of the unit root test is calculated at the first and second differences. The ADF test and the corresponding p-value are -5.3241 and 0.01, respectively. The p-value for the ADF test is under the rejection region; that is p-value is less than the test critical values at $\alpha = 5\%$. It examines that data is stationary, and the alternative hypothesis is accepted at a 5% significance level. The results show that data is stationary on the first difference.

Model Identification

In the model identification stage of ARIMA (p, d, q), the primary objective is to select suitable values for the three parameters, p, d, and q. If the series exhibits a trend, there are two possible methods to consider. One is to apply the difference to eliminate the trend, while the other is to employ a regression model to capture and remove the trend. Ultimately, the aim is to determine the best approach to uncover the underlying patterns and dependencies within the data, leading to more accurate forecasting outcomes. While many writers prefer deterministic trend removal, Box-Jenkins seems to favor differencing. The initial step in either scenario is examining the plots of auto-correlations function (ACF) and partial auto-correlation function (PACF).

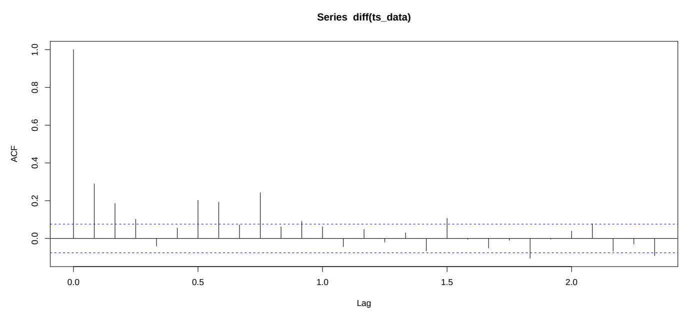

Figure 4. ACF plot of the differenced series

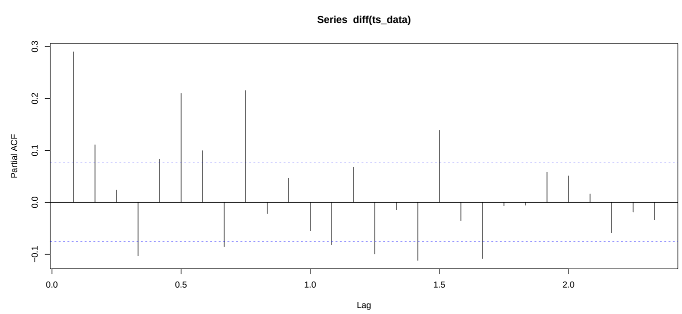

Figure 5. PACF plot of the differenced series

Figures 4 and 5 display the plots of the ACF and PACF, respectively. By analyzing these plots, we propose potential ARIMA models with specific parameter values for (p, d, q). A total of fourteen ARIMA models have been suggested, as outlined in Table 1.

Table 1. Forecast Errors from ARIMA (p, d, q) Models

Model	AIC	BIC	HQIC	RMSE
ARIMA(2,1,2)	2927.65	2950.17	2936.38	2.1601
ARIMA(2,1,3)	2908.32	2935.33	2918.78	2.1258
ARIMA(2,1,4)	2910.29	2941.81	2922.50	2.1258
ARIMA(3,1,2)	2911.12	2938.14	2921.59	2.1303
ARIMA(3,1,3)	2910.28	2941.79	2922.49	2.1258
ARIMA(3,2,4)	2887.11	2923.13	2901.06	2.0869
ARIMA(4,1,2)	2911.89	2943.42	2924.11	2.1284
ARIMA(4,2,3)	2890.40	2926.42	2904.36	2.0923
ARIMA(4,2,4)	2888.76	2929.29	2904.46	2.0864
ARIMA(5,2,1)	2920.49	2952.00	2932.69	2.1463
ARIMA(5,2,2)	2921.35	2957.37	2935.30	2.1444
ARIMA(5,2,3)	2889.95	2930.48	2905.65	2.0883
ARIMA(5,2,4)	2890.76	2935.79	2908.21	2.0864
ARIMA(5,2,5)	2888.45	2937.98	2907.64	2.0794

Table 1 presents the forecast errors of the previously discussed ARIMA models, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Mean Squared Error (MSE), and Hannan-Quinn Information Criterion (HQIC). The ARIMA(3,2,4) and ARIMA(5,2,5) models exhibit superior performance, as evidenced by their forecast error values, which are lower than those of the other models in the table. Therefore, these models are recommended as the most suitable for forecasting purposes. The forecast plots for ARIMA(3,2,4) and ARIMA(5,2,5) are provided in Figures 6 and 7, respectively.

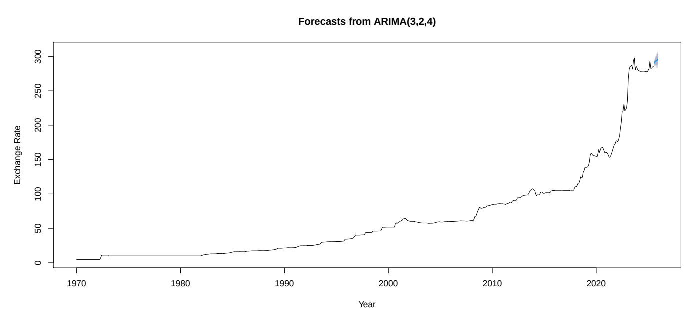

Figure 6. Forecast From ARIMA(3,2,4)

In the next section, we will forecast the currency exchange rate using various machine learning algorithms, including HE, NN, MLP, and the Facebook

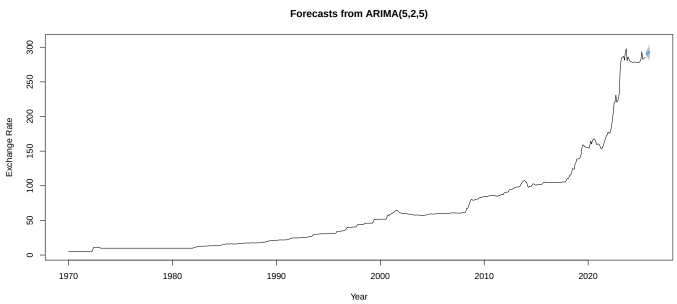

Figure 7. Forecast From ARIMA(5,2,5)

Prophet model. These models are designed to capture complex patterns and non-linear trends in the data, providing a more advanced approach to forecasting. So far, we have been using classical models, such as ARIMA, to predict the exchange rate, but we aim to explore more robust, data-driven methods in this section.

4.3 Machine Learning Algorithms

In our analysis, we used the full dataset without splitting it into separate training or testing datasets, as our goal was to train all machine learning models using the complete data and then apply forecasting. This approach was specifically chosen to allow for a fair comparison between machine learning models, such as NN and Holt ES, with classical models like ARIMA. By utilizing the entire dataset in each model, we ensured consistency across the different methods. For the Holt ES and NN models, we employed a trial-and-error approach to determine the optimal values for alpha and beta. These values were selected based on where the variance in both the NN and Holt ES models became smaller, ensuring improved model stability. The details of this process, including how these values were determined, can be found in the Holt ES section. It is important to note that the machine learning model implementation did not involve separate training/validation splits, and we did not perform traditional hyperparameter tuning. Instead, we focused on using the entire dataset and optimizing the key parameters through trial and error. This approach allowed us to directly apply all models to the complete dataset for forecasting, facilitating a meaningful comparison of the machine learning models with the classical ARIMA model. However, it should be noted that the absence of explicit training and validation splits may limit some aspects of model evaluation.

Exponential Smoothing

ETS is a univariate time series forecasting technique that may be expanded to include data with seasonal or systematic patterns. It is an effective forecasting technique that can replace the famous Box-Jenkins ARIMA family of techniques. ES time series forecasting methods are classified into three types. An expansion that specifically addresses trends, the most sophisticated form with support for seasonality, and a straightforward technique with no systematic structure. This paper will only look at the second type of ES, also known as double ES or Holt's ES. Holt ES or DES is an ES extension explicitly supporting trends in univariate time series. To manage the trend change, a second smoothing factor called β is introduced along with the α parameter that controls the smoothing factor for the level. Depending on whether a trend is linear or exponential, the approach can accept changes in either an additive or multiplicative fashion. In honor of the method's developer, Charles Holt, DES with an additive trend is often referred to as Holt's linear trend model with no seasonality.

This paper employs the trial-and-error method to determine the optimal values for the α and β parameters. Following the approach outlined in [2], the appropriate values for α and β are selected based on the minimization of the MAPE, MAE, and MSE. In this study, the standard values of α = 0.9999 and β = 0.3041, identified using the holt function in *R*, were initially utilized. However, the β parameter was subsequently tuned to identify the value that minimizes forecasting error. It was found that, among all possible values of β (ranging from 0.0001 to 0.5), β = 0.3041 resulted in the lowest MAE and MAPE. Therefore, the aforementioned values for α and β are selected for forecasting purposes. For further details, please refer to [2, 42, 57–60] and the references cited therein.

The smoothing plot determines whether the selected model fits the data accurately. If the works

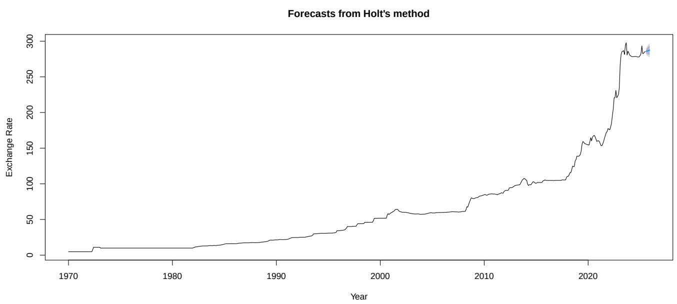

Figure 8. Forecast From Holt Exponential Model

closely follow the actual data, the model is assumed to fit the data. Figure 8 shows the plot of forecast values of the DES model with a 95% confidence interval. As a measure of the accuracy of the forecasts, MSE, MAE, and MAPE are calculated which are given in Table 2. It can be seen that the MSE, MAPE, and MAE of the DES model are less than a classical model for time series analysis, ARIMA.

Artificial Neural Network

The ANN technique, often called NN, is a computational technique that has recently made substantial progress. The NN in a number of scientific fields has shown its ability to handle various problems. The NN's have a powerful ability known as universal approx. People have been considerably interested in using ANN for forecasting and modeling data in recent years. Such as [44] applied neural networks in the stock market. The NNAR technique is a solid alternative to ARIMA models. It works in the same way as the biological neurons signal to one another. A neural network's advantage is its ability to learn from the inputs given and train itself from the data, optimizing the weights for a better prediction. In the same way that we used lagged values in a linear auto-regression model, lagged values of time series data can be used as inputs to a neural network. It is known as an NNAR model or neural network auto-regression. Both p and k are components of the NNAR. Where k indicates the number of hidden nodes present, and p suggests the quantity of lagged values used as inputs. NNAR is used to formally represent the output (p, k). A Similar notation is used if the dataset is seasonal, i.e., NNAR(p, P, k), where P denotes the number of seasonal lags and p is chosen using an information criterion, such as the AIC. The forecast of NNAR is presented in Figure 9 using p = 1 lagged value and k = 1 hidden node. The forecast error and the forecasted values of NNAR are given in Table 2 and Table 4, respectively.

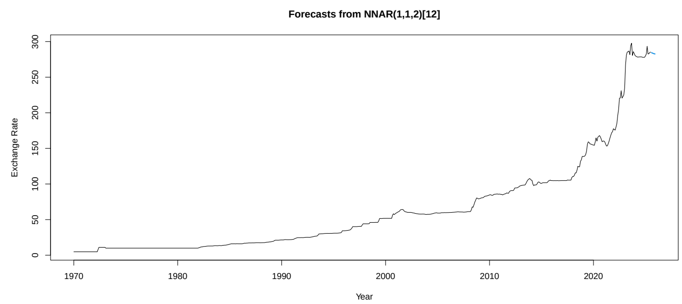

Figure 9. Forecast From NNAR(1,1,2)

Multilayer Perceptron

A MLP is an ANN composed of multiple interconnected layers of neurons, including an input layer, one or more hidden layers, and an output layer. The neurons in each layer process and transmit information in a feed-forward manner, using nonlinear activation functions in the hidden layers to transform input signals. This enables the MLP to learn and represent intricate relationships between input and output data, making it useful for tasks such as classification, pattern recognition, and prediction.

Data flows forward from input to output layer in an MLP, comparable to a feed forward network. The backpropagation technique is utilized to train neurons within the MLP. Errors will be propagated back until the MSE is minimized. From Figure 10, the output indicates that the resulting network has 10 input nodes, 5 hidden nodes, and the Gray input nodes are auto-regressions. The forecast from MLP algorithm using the aforesaid nodes, is given in Figure 11. The forecast errors and the forecasted value from this algorithm are given in Table 2 and Table 4, respectively.

The Facebook Prophet Model

A critical component of data analysis that aids companies and organizations in making defensible decisions

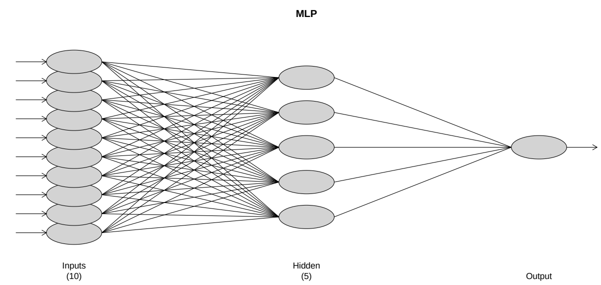

Figure 10. Hidden Nodes

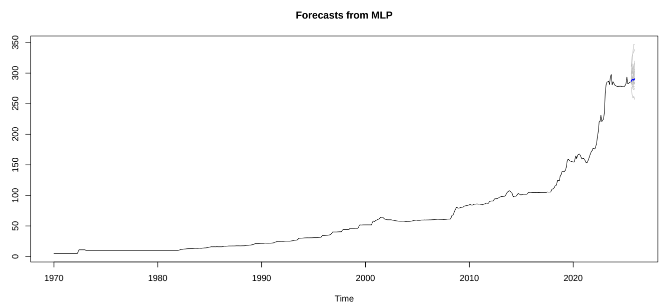

Figure 11. Forecast from MLP

by drawing on historical trends and patterns is time series forecasting. Planning, forecasting, and decision-making in a variety of businesses depend on the ability to accurately predict future trends and patterns in time series data. Time series data may be forecasted using a variety of techniques, but Prophet model is a well-liked algorithm because of its precision, adaptability, and simplicity of use. The five months ahead forecast from Prophet model is given in the following graph: The Figure 12 shows the exchange rate from

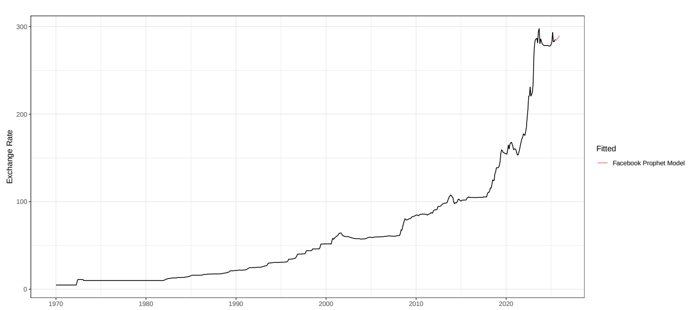

Figure 12. Forecast From Facebook Prophet Model

1970 to 2025, with predictions from the Facebook Prophet Model. The model suggests a slight increase in the exchange rate, as indicated by the fitted values, which track the overall trend in the historical data. All analyses were conducted in R 4.3.0 using RStudio, with packages forecast, tseries, prophet, neuralnet, and nnet.

5 Comparison between ARIMA, ES, NN, and Facebook Prophet Models

The MAE, MSE, and MAPE are a few of the metrics used to compare performance and select the optimal approach among the underlying algorithms. In this paper, the model's performance is assessed using each of these criteria.

In statistical models, the MSE quantifies the coefficient of error terms. The average square of the discrepancies between the actual and anticipated data values is evaluated. The mean error between the predicted and observed values is determined by the MAE, and the zero value of the error term indicates that the MSE is equal to zero. On the other hand, the RMSE, or root of the MSE, is the value of the MSE. Finally, the absolute mean percentage error for the data is measured using the MAPE. These models may be expressed mathematically by the following equations:

$$\text{MAE} = \frac{1}{N_t}\sum_{n=1}^{N_t} |d_n - y_n| \,, \tag{10}$$

$$\text{RMSE} = \sqrt{\frac{1}{N_t}\sum_{n=1}^{N_t} (d_n - y_n)^2}, \tag{11}$$

$$\text{MAPE} = \frac{100}{N_t}\sum_{n=1}^{N_t} \left|\frac{d_n - y_n}{d_n}\right|, \tag{12}$$

$$\text{AIC} = 2k - 2\ln(L), \tag{13}$$

$$\text{BIC} = \ln(n)k - 2\ln(L), \tag{14}$$

in which, d_n and y_n denote observed and model value respectively where n are number of observations, k are number of parameters and L is the likelihood of the model. The values of RMSE, MAE, MAPE, AIC, and BIC using ARIMA, ES, Facebook Prophet and NN models are computed using the expressions given above. The comparison of different models using RMSE, MAE and MAPE is reported in Table 2.

Table 2. Comparison between ARIMA, and Machine learning Models

Author	Model	RMSE	MAE	MAPE
	ARIMA(3,2,4)	2.0869	0.7937	1.0397
	ARIMA(5,2,5)	2.0794	0.7872	1.0385
	Holt ES	2.2967	0.9183	2.2118
	NNAR	2.0230	0.7747	1.2397
	MLP	0.9359	0.4426	1.0527
	Prophet	13.281	4.3518	1.7706
[46]	ARIMA	0.0410	–	4.8660
	ES	0.0530	–	6.3050
	ANN	0.0480	–	5.4430
[40]	ARIMA	14.630	10.020	5.79
[1]	ARIMA	0.1273	0.0845	3.89

From Table 2, it is evident that the machine learning algorithm, MLP, demonstrates superior efficiency when compared to the classical Box-Jenkins methodology, ARIMA. Specifically, the values of MSE, MAE, and MAPE are all lower for the MLP model than for the ARIMA model. Furthermore, it is observed that other machine learning algorithms, such as NNAR and Holt ES, exhibit performance close to that of ARIMA with respect to the aforementioned error metrics. This suggests that, for complex univariate time series, the aforementioned machine learning algorithms may outperform the traditional Box-Jenkins methodology. Additionally, [40] applied ARIMA and machine learning models to forecast exchange rates. However, our models exhibit the lowest forecast errors in comparison. Similarly, [1, 46] utilized both classical and machine learning models for exchange rate forecasting, but our models again yield the lowest forecast errors, as demonstrated in Table 2.

To evaluate model generalization performance, the full dataset was divided into 80% training and 20% testing subsets while preserving temporal order (i.e., no random shuffling). The training subset was used to fit each model, and predictions were generated for the remaining 20% testing period. Model performance was then assessed using three standard error metrics: RMSE, MAE, and MAPE.

Table 3. Model performance on testing dataset (20% of total data)

Model	RMSE	MAE	MAPE (%)
ARIMA(3,2,4)	2.4821	0.9324	1.2916
ARIMA(5,2,5)	2.4368	0.9145	1.2764
Holt's ES	2.6837	1.0221	2.5712
NNAR	2.3492	0.8898	1.3983
MLP	1.1894	0.5376	1.2365
Prophet	14.618	4.9128	2.0847

When trained on 80% of the dataset and tested on the remaining 20%, the MLP achieved the best predictive accuracy (RMSE = 1.1894, MAE = 0.5376, MAPE = 1.2365%), followed by the NNAR model. The ARIMA(5,2,5) slightly outperformed ARIMA(3,2,4), while Holt's ES and Prophet showed comparatively higher error values. Model tuning was conducted as follows: ARIMA orders (p,d,q) were selected via AIC and BIC minimization;For Holt's ES, β = 0.9 was used. ANN and MLP models employed one hidden layer with 10 neurons, a logistic activation function, a learning rate of 0.01, backpropagation training, 1000 iterations, and SSE as the loss function. These settings were chosen through experimentation to ensure reproducibility and reliable forecasting performance. Overall, machine learning models, particularly MLP, demonstrated superior generalization and adaptability to nonlinear temporal patterns, confirming their robustness compared with classical time series models under an 80:20 data split.

The selection and implementation of an appropriate forecasting methodology have always been critical considerations in the planning and control processes of both businesses and government agencies. Specifically, in the context of Pakistan, effective monetary policy management is essential to prevent exchange rate instability and safeguard exporters from the risks of losing their equity. To mitigate exchange rate uncertainty, it is imperative to control or forecast exchange rates as part of the broader goal of economic development. Consequently, this study aims to forecast Pakistan's exchange rate for the next five months using the aforementioned models and algorithms. The forecasted values generated by the various models are presented in Table 4.

Table 4. Forecast based on ARIMA, ES, Prophet and NN Models

Model	Aug	Sep	Oct	Nov	Dec
ARIMA(3,2,4)	290.43	292.77	293.68	293.85	296.13
ARIMA(5,2,5)	289.85	291.36	291.74	291.57	293.66
Holt ES	285.72	286.14	286.56	286.98	287.41
MLP	286.79	289.04	289.57	288.58	290.59
NNAR	284.48	283.85	283.35	282.96	282.64
Prophet	285.13	285.99	288.46	288.93	288.47

The forecasted values of different Model/Algorithms provided in Table4 are plotted. The Figure 13 compares various forecasting models for exchange rates from Jan 1970 to Jul 2025. The models, including

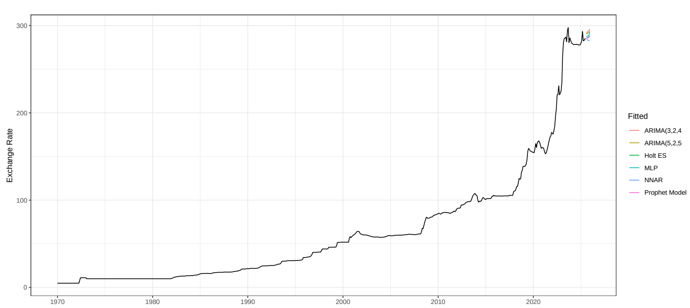

Figure 13. Forecast From Suggested Models

ARIMA(3,2,4), ARIMA(5,2,5), Holt ES, MLP, NNAR, and Prophet, suggest a slight decrease in the exchange rate, with NNAR predicting the most significant drop. The proximity of the fitted lines to the actual data indicates the accuracy of each model's forecast.

Limitation

This study is based on univariate data that spans from 1970 to July 2025, focusing on a single variable without incorporating external factors. While this approach provides valuable insights, it is important to acknowledge the limitations of using only univariate models. The absence of external variables, such as macroeconomic indicators (e.g., GDP growth, inflation rates, and unemployment), demographic factors, technological advancements, and policy changes, means that the analysis does not account for broader contextual influences that may impact the studied variable. Additionally, global events, environmental factors, and social or cultural shifts may also have significant effects that are not captured in this model. Future research could expand the scope of analysis by incorporating these external variables to provide a more comprehensive understanding of the subject matter. In this study, both classical univariate time series models and machine learning models were first trained using the complete dataset to ensure a consistent comparison of their in-sample fitting performance. Subsequently, to assess their generalization capability, an 80:20 train–test split was applied, where 80% of the data were used for model training and the remaining 20% for testing. Forecasts were generated for the testing period, and the corresponding error metrics (RMSE, MAE, and MAPE) were computed to evaluate predictive accuracy on unseen data given in Table 3. This dual evaluation approach provides a more comprehensive understanding of model performance, allowing comparison of both fitting and forecasting abilities under identical experimental conditions.

6 Conclusion

The exchange rate of a country serves as a key indicator of its economic standing on the international stage and plays a vital role in maintaining internal economic stability. It also significantly influences foreign investment. This study focuses on forecasting the national currency exchange rate of Pakistan using three methodologies: the Box-Jenkins (ARIMA) model, DES, and various machine learning algorithms, including the MLP. The findings reveal that machine learning algorithms performed well, with MLP outperforming both the classical ARIMA model and other machine learning techniques by yielding the lowest forecast errors. Additionally, the forecasted values generated by MLP closely align with the actual values, as illustrated in Figure 12, highlighting its robustness in modeling complex time series data. Notably, the forecast errors of the proposed models in this study are also lower than those reported in other comparative studies listed in Table 2. Based on the trends shown in Figure 12, it can be inferred that the national currency exchange rate of Pakistan is expected to slightly rise in the coming months. In conclusion, exchange rates hold significant importance as they influence global trade, investment decisions, tourism, monetary policy, and currency risk management. Therefore, understanding exchange rate dynamics is crucial for stakeholders in international business and finance. This study contributes valuable insights into the projected demand for domestic currency in the foreseeable future. It is also helpful for the government and policymakers. It is important to note that when the currency exchange rate rises, several options can be utilized to tackle the situation and stabilize it. Some possible actions include: (1). The central bank can adjust the interest rates to influence the demand for the currency. (2). The government can intervene in the foreign exchange market by buying its own currency and utilizing foreign reserves. (3). The government can adjust its fiscal policies, such as taxation and government spending, to influence the exchange rate. (4). Long-term structural reforms can enhance the competitiveness of the economy. Moreover, the specific measures implemented would depend on the prevailing economic conditions, policy objectives, and available policy tools.

Future Works

In future work, we can apply regime-based time series modeling, as our data may contain structural changes, evident in Figure 1. This approach involves identifying breakpoints, caused by policy shifts, economic events, or government changes, and dividing the series into segments with similar behavior. Different models can then be applied to each segment, such as ARIMA for stable periods and MLP or LSTM for volatile phases. The segmented forecasts can be combined to improve overall accuracy, offering a more robust framework for capturing dynamic patterns in exchange rate data. Additionally, future research can focus on developing and refining models that capture the complex dynamics and determinants of exchange rates. Comparative analysis of currency exchange rates across different countries can also be explored. Moreover, examining the interactions between exchange rates and financial markets, including stock markets, bond markets, and foreign exchange markets, could provide deeper insights into the broader economic implications.

Author Contributions

Urva Zainab: Conceptualization, Methodology, Software **Attra Ali**: Data curation, Writing- Original draft preparation. **Kifayat Ullah**: Visualization, Investigation. **Emal Hanafi**: Software, Validation. **Palwasha Seher**: Writing- Reviewing and Editing

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

Funding Information

This research did not receive any specific grant from funding agencies in the public, commercial, or not for-profit sectors.

References

[1] S. I. Abir, S. A. Al Shiam, R. M. Zakaria, A. H. Shimanto, S. S. Arefeen, M. S. A. Dolon, N. Sultana, and S. Shoha, "Use of AI-powered precision in machine learning models for real-time currency exchange rate forecasting in BRICS economies," *Journal of Economics, Finance and Accounting Studies*, vol. 6, no. 6, pp. 66–83, 2024.

[2] R. Aminudin and Y. Putra, "Poverty line forecasting model using double exponential smoothing Holt's method," *IOP Conference Series: Materials Science and Engineering*, vol. 662, p. 062007, 2019.

[3] M. Arif, M. Abbas, M. A. Shehzad, Z. Batool, M. Rabia, and A. M. Soomro, "An ensembling approach to predict hepatitis in patients with liver disease using machine learning," *VFAST Transactions on Software Engineering*, vol. 11, no. 3, pp. 42–52, 2023.

[4] M. Arif, M. A. Aslam, H. U. Rehman, M. Abbas, and S. Bukhari, "Laboratory diagnostic pathways using machine learning," *VFAST Transactions on Software Engineering*, vol. 10, no. 1, pp. 78–85, 2022.

[5] A. Azadeh, S. F. Ghaderi, and S. Sohrabkhani, "A simulation-based neural network algorithm for forecasting electrical energy consumption in Iran," *Energy Policy*, vol. 36, no. 7, pp. 2637–2644, 2008.

[6] D. E. Babatunde, "Artificial neural network and its applications in the energy sector: An overview," Tech. Rep. 670216917, 2020.

[7] N. Badar, H. Fatima, A. Jabbar, and M. Asif, "Major food crops production and yield forecast in Pakistan," *Pakistan Journal of Agricultural Research*, vol. 28, no. 3, 2015.

[8] N. Barkhomay, "The exchange rate volatility and trade balance: Case of Uzbekistan," *Journal of Applied and Business Research (JAEBER)*, vol. 1, no. 3, pp. 149–161, 2011.

[9] V. Bartoš, M. Vochozka, and V. Sanderová, "Copper and aluminium as economically imperfect substitutes, production and price development," *Acta Montan Slovaca*, vol. 27, pp. 462–478, 2022.

[10] P. H. Borghi, O. Zakordonets, and J. P. Teixeira, "A COVID-19 time series forecasting model based on MLP ANN," *Procedia Computer Science*, vol. 181, pp. 940–947, 2021.

[11] G. Box, G. M. Jenkins, and G. C. Reinsel, "Time series analysis: Forecasting and control," 3rd ed., Hoboken, NJ: Wiley, 1994.

[12] G. Box and G. Jenkins, "Time series analysis, forecasting and control," Revised ed., 1976 ed., Englewood Cliffs, NJ: Prentice Hall, 1990.

[13] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," *arXiv preprint arXiv:1412.3555*, 2014.

[14] J. G. de Gooijer and R. J. Hyndman, "25 years of time series forecasting," *International Journal of Forecasting*, vol. 22, no. 3, pp. 443–473, 2006.

[15] S. Edwards, "Real exchange rates in the developing countries: Concepts and measurement," Tech. Rep., 1989.

[16] B. Eichengreen, "Real exchange rate and economic growth," *Social and Economic Studies*, vol. 56, no. 4, pp. 7–20, 2008.

[17] M. Elsaraiti and A. Merabet, "A comparative analysis of the ARIMA and LSTM predictive models and their effectiveness for predicting wind speed," *Energies*, vol. 14, no. 20, p. 6782, 2021.

[18] E. Erdogdu, "Natural gas demand in Turkey," *Applied Energy*, vol. 87, no. 1, pp. 211–219, 2010.

[19] I. A. Faheem-ul Hussain Dehraj and M. A. Channa, "The impact of exchange rate fluctuation on imports and exports of Pakistan: Time series analysis from 1985–2015," *International Journal of Management Sciences and Business Research*, 2017.

[20] F. N. Fauziah, A. Gunaryati, and R. T. K. Sari, "Comparison forecasting with double exponential smoothing and artificial neural network to predict the price of sugar," *Int. J. Simul. Syst. Sci. Technol.*, vol. 18, no. 4, pp. 11–13, 2017.

[21] R. Fullér, "Neural fuzzy systems," Tech. Rep., 1995.

[22] P. Gala and C. R. Lucinda, "Exchange rate misalignment and growth: Old and new econometric evidence," *Revista Economia*, vol. 7, no. 4, pp. 165–187, 2006.

[23] G. Goverdhan, S. Khare, and R. Manoov, "Time series prediction: Comparative study of ML models in the stock market," Tech. Rep., 2022.

[24] E. Y. Hamid and M. H. O. Abushaba, "Use of exponential Holt model and the Box-Jenkins methodology in predicting the time series of cement production in Sudan," *Journal of Al-Qadisiyah for Computer Science and Mathematics*, vol. 12, no. 1, pp. –42, 2020.

[25] J. V. Hansen, J. B. McDonald, and R. D. Nelson, "Time series prediction with genetic algorithm designed neural networks: An empirical comparison with modern statistical models," *Computational Intelligence*, vol. 15, no. 3, pp. 171–184, 1999.

[26] M. Irfan, M. Irfan, and M. Tahir, "Modeling the province-wise yield of rice crop in Pakistan using GARCH model," *International Journal of Science and Technology*, vol. 1, no. 6, pp. 224–228, 2011.

[27] P. S. Kalekar et al., "Time series forecasting using Holt-Winters exponential smoothing," Tech. Rep., Kanwal

Rekhi School of Information Technology, 4329008(13), pp. 1–13, 2004.

[28] M. Kandil and I. Mirzaie, "The effects of exchange rate fluctuations on output and prices: Evidence from developing countries," *The Journal of Developing Areas*, pp. 189–219, 2005.

[29] A. J. Khan, P. Azim, and S. H. Syed, "The impact of exchange rate volatility on trade: A panel study on Pakistan's trading partners," *The Lahore Journal of Economics*, vol. 19, no. 1, p. 31, 2014.

[30] M. Khashei and M. Bijari, "An artificial neural network (p, d, q) model for time series forecasting," *Expert Systems with Applications*, vol. 37, no. 1, pp. 479–489, 2010.

[31] M. Khashei, M. Bijari, and G. A. R. Ardali, "Improvement of auto-regressive integrated moving average models using fuzzy logic and artificial neural networks (ANNs)," *Neurocomputing*, vol. 72, no. 4–6, pp. 956–967, 2009.

[32] P. R. Lane and G. M. Milesi-Ferretti, "External wealth, the trade balance, and the real exchange rate," *European Economic Review*, vol. 46, no. 6, pp. 1049–1071, 2002.

[33] C. Lee, Y. Sehwan, and J. Jongdae, "Neural network model versus SARIMA model in forecasting Korean stock price index (KOSPI)," *Issues in Information Systems*, vol. 8, no. 2, pp. 372–378, 2007.

[34] S. Liang, T. Deng, A. Huang, N. Liu, and X. Jiang, "Energy consumption prediction using the GRU-MMAttention-LightGBM model with features of Prophet decomposition," *PLOS ONE*, vol. 18, no. 1, p. e0277085, 2023.

[35] S. Lima, A. M. Gonçalves, and M. Costa, "Time series forecasting using Holt-Winters exponential smoothing: An application to economic data," in *AIP Conference Proceedings*, vol. 2186, p. 090003, AIP Publishing LLC, 2019.

[36] A. Malki, E.-S. Atlam, and I. Gad, "Machine learning approach of detecting anomalies and forecasting time-series of IoT devices," *Alexandria Engineering Journal*, vol. 61, no. 11, pp. 8973–8986, 2022.

[37] A. Meyler, G. Kenny, and T. Quinn, "Forecasting Irish inflation using ARIMA models," Tech. Rep., 1998.

[38] M. Navratil and A. Kolkova, "Decomposition and forecasting time series in the business economy using Prophet forecasting model," *Central European Business Review*, vol. 8, no. 4, p. 26, 2019.

[39] V. R. Prybutok, J. Yi, and D. Mitchell, "Comparison of neural network models with ARIMA and regression models for prediction of Houston's daily maximum ozone concentrations," *European Journal of Operational Research*, vol. 122, no. 1, pp. 31–40, 2000.

[40] M. Qureshi, N. Ahmad, S. Ullah, and A. R. ul Mustafa, "Forecasting real exchange rate (REER) using artificial intelligence and time series models," *Heliyon*, vol. 9, no. 5, 2023.

[41] M. Rabia, Z. Rashid, F. Babar, and M. Abbas, "Forecasting of pesticide usage in Pakistan: An application of the univariate ARIMA model and artificial neural network," *Nativa*, vol. 13, no. 1, 2025.

[42] A. Rahamneh and A. A. Ali, "Using single and double exponential smoothing for estimating the number of injuries and fatalities resulted from traffic accidents in Jordan (1981–2016)," *Middle-East Journal of Scientific Research*, vol. 25, no. 7, pp. 1544–1552, 2017.

[43] Z. Rowland, A. Blahova, and G. Peng, "Silver as a value keeper and wealth distributor during an economic recession," *Acta Montanistica Slovaca*, vol. 26, no. 4, 2021.

[44] E. Schöneburg, "Stock price prediction using neural networks: A project report," *Neurocomputing*, vol. 2, no. 1, pp. 17–27, 1990.

[45] H. K. Sharma, K. Kumari, and S. Kar, "Short-term forecasting of air passengers based on hybrid rough set and double exponential smoothing models," *Intelligent Automation and Soft Computing*, vol. 25, no. 1, pp. 1–13, 2019.

[46] M.-L. Shen, C.-F. Lee, H.-H. Liu, P.-Y. Chang, and C.-H. Yang, "An effective hybrid approach for forecasting currency exchange rates," *Sustainability*, vol. 13, no. 5, p. 2761, 2021.

[47] R. Siddiqui and N. Akhtar, "The impact of changes in exchange rate on prices: A case study of Pakistan," *The Pakistan Development Review*, pp. 1059–1066, 1999.

[48] C. E. Smith, "Exchange rate variation, commodity price variation and the implications for international trade," *Journal of International Money and Finance*, vol. 18, no. 3, pp. 471–491, 1999.

[49] V. Soloviev, N. Titov, and E. Smirnova, "Coking coal railway transportation forecasting using ensembles of

ElasticNet, LightGBM, and Facebook Prophet," in *Machine Learning, Optimization, and Data Science: 6th International Conference, LOD 2020, Siena, Italy, July 19–23, 2020, Revised Selected Papers, Part II*, vol. 6, pp. 181–190, Springer, 2020.

[50] S. J. Taylor and B. Letham, "Forecasting at scale," *The American Statistician*, vol. 72, no. 1, pp. 37–45, 2018.

[51] U. Thakur, S. K. Singh, S. Kumar, H. Singh, V. Arya, B. B. Gupta, R. W. Attar, A. Alhomoud, and K. T. Chui, "Advanced web traffic modelling and forecasting with a hybrid predictive approach," *Journal of Web Engineering*, vol. 24, no. 3, pp. 409–456, 2025.

[52] B. V. Vishwas and A. Patel, *Hands-on Time Series Analysis with Python: From Basics to Bleeding Edge Techniques*, Apress, 2020.

[53] M. Vochozka, F. Petrách, and S. Janek, "Changes in perception of coffee in EU: Luxury good turned inferior," *Economics & Sociology*, vol. 15, no. 3, pp. 248–267, 2022.

[54] J. Yao, C. L. Tan, and H.-L. Poh, "Neural networks for technical analysis: A study on KLCI," *International Journal of Theoretical and Applied Finance*, vol. 2, no. 02, pp. 221–241, 1999.

[55] G. Yu and Z. Schwartz, "Forecasting short time-series tourism demand with artificial intelligence models," *Journal of Travel Research*, vol. 45, no. 2, pp. 194–203, 2006.

[56] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, 2003.

[57] A. Riaz, N. R. Chaudhry, R. Choudhary, M. Riaz, and M. Suhail, "Capital Asset Pricing Model for the stock market in Pakistan," *Qlantic Journal of Social Sciences*, vol. 5, no. 2, pp. 76–84, 2024.

[58] Lim, B, and Zohren, S, "Time-series forecasting with deep learning: a survey." *Philosophical Transactions of the Royal Society A*, vol. 379, pp. 20200209, 2021.

[59] Torres, J. F., Hadjout, D., Sebaa, A., Martínez-Álvarez, F., & Troncoso, A, "Deep learning for time series forecasting: a survey," *Big data*, vol. 9, pp. 3–21, 2021.

[60] Masini, R. P., Medeiros, M. C., & Mendes, E. F., "Machine learning advances for time series forecasting", *Journal of economic surveys*, vol. 37, pp. 76–111, 2023.

[61] Benidis, K., Rangapuram, S. S., Flunkert, V., Wang, Y., Maddix, D., Turkmen, C., ... & Januschowski, T, "Deep learning for time series forecasting: Tutorial and literature survey" *ACM Computing Surveys*, vol. 55, pp. 1–36, 2022.

[62] Wang, Z., Kong, F., Feng, S., Wang, M., Yang, X., Zhao, H., ... & Zhang, Y, "Is mamba effective for time series forecasting?", *Neurocomputing*, vol. 619, pp. 129178, 2025.

[63] Zeng, A., Chen, M., Zhang, L., & Xu, Q, "Are transformers effective for time series forecasting?" *In Proceedings of the AAAI conference on artificial intelligence*, vol. 37, pp. 11121–11128, 2023.

[64] Godahewa, R., Bergmeir, C., Webb, G. I., Hyndman, R. J., & Montero-Manso, P, "Monash time series forecasting archive" *arXiv preprint arXiv:2105.06643*, 2021.

[65] Shmueli, G., & Polak, J, "Practical time series forecasting with r: A hands-on guide", *Axelrod schnall publishers*, 2024.

[66] Lin, S., Lin, W., Wu, W., Chen, H., & Yang, J, "Sparsetsf: Modeling long-term time series forecasting with 1k parameters", *arXiv preprint arXiv:2405.00946*, 2024.

[67] Yi, K., Zhang, Q., Fan, W., Wang, S., Wang, P., He, H., ... & Niu, Z, "Frequency-domain MLPs are more effective learners in time series forecasting", *Advances in Neural Information Processing Systems*, vol. 36, pp. 76656–76679, 2023.

[68] Qiu, X., Li, X., Pang, R., Pan, Z., Wu, X., Yang, L., ... & Yang, B, "Easytime: Time series forecasting made easy" *In 2025 IEEE 41st International Conference on Data Engineering (ICDE)*, pp. 4564–4567, 2025.

[69] Li, Z., Qi, S., Li, Y., & Xu, Z, "Revisiting long-term time series forecasting: An investigation on linear mapping", *arXiv preprint arXiv:2305.10721*, 2023.