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**Foreign Currency Exchange Rate Prediction Using Models Consisting of ARIMA and Random Forest**


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# Abstract

Foreign currency refers to the cash of a different country than the one in which a budgetary transaction occurs. The impact on global commerce and investments can affect exchange rates, trade balances, and economic stability, influencing global economic dynamics. Foreign currency exchange platforms integrate machine learning and deep learning algorithms, which allows for improved risk management and investing decisions. These methodologies take into account current market trends, geopolitical effects, and big data, resulting in a more informed and adaptable approach to the ever-changing currency landscape. This chapter proposes two machine learning algorithms Autoregressive Integrated Moving Average (ARIMA) and random Forest Regression (RFR) and combines the predictions from both models to create a hybrid forecast. The authors use Mean absolute error (MAE), Mean squared error (MSE), Root Mean Squared Error (RMSE), and mean absolute percentage error (MAPE) to measure the performance of the algorithms. Empirical analysis is used to assess the effectiveness of the proposed hybrid model, showing less error than others for forecasting foreign exchange rates. This study is useful for the stakeholders to set a wide range of approaches for the foreign exchange market.

## Declaration by author

We declare that this thesis is an original report of our research, has been written by me and has not been submitted for any previous degree. To the best of our knowledge, this thesis only includes information that has been properly acknowledged and hasn't been published by anybody else before. Nothing in this thesis, whether in English or another language, has been approved as a component of the requirements for any other academic degree or non-degree program.

This is an exact replica of the thesis, complete with the last edits.


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# Approval

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## Publications included in this thesis

Still Our thesis paper hasn't published any journals. We are trying to publishing it as early as possible.

## Submitted manuscripts included in this thesis

We have no journal publications.

## Other publications during candidature

No publications yet.

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# Research Contributions and Ethical Considerations

Enumerate the important and noteworthy contributions that the various authors contributed to the study, writing, and/or research that is shown in the thesis. These might include noteworthy contributions to the project's conception and design; specialized technical work; analysis and interpretation of research data; and the writing of substantial portions of the work or their critical revision in order to support the interpretation.

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## Keywords

Foreign Currency Exchange, Currency Rate, Machine Learning, Autoregressive Integrated Moving Average (ARIMA), Random Forest.

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## List of Abbreviations and Symbols

Predicting foreign currency exchange rates is a critical component of financial decision-making, as it impacts international trade and investment. In order to improve the accuracy of exchange rate predictions, we provide a hybrid model in this work that combines Random Forest and Autoregressive Integrated Moving Average (ARIMA). While Random Forest uses the strength of ensemble learning to handle non-linear relationships and feature interactions, the ARIMA model captures the temporal dependencies in the data. The goal of the two models' synergistic integration is to produce a forecasting framework that is more trustworthy and robust.

### List of Symbols:

**FX:** Foreign Exchange

**ARIMA:** Autoregressive Integrated Moving Average

**RF:** Random Forest

**USD:** United States Dollar

**EUR:** Euro

**GBP:** British Pound Sterling

**CAD:** Canadian Dollar

**AUD:** Australian Dollar

**RMSE:** Root Mean Square Error

**MAE:** Mean Absolute Error

**MSE:** Mean Squared Error

**R2:** R-squared (Coefficient of Determination)

**VAR:** Vector Autoregression

**MAPE:** Mean Absolute Percentage Error

**PCA:** Principal Component Analysis

**CV:** Cross-Validation

**ML:** Machine Learning

**API:** Application Programming Interface

**KPI:** Key Performance Indicator

# Chapter 1

# Introduction

## 1.1 Background

In international financial research, the exchange rate problem has long been a popular subject. The exchange rate plays a significant role in the economy and affects all major markets to some extent [1]. The foreign currency market, which has the largest level of liquidity globally, is one of the principal financial markets [2]. In the modern period of open economies and rising competition in an interconnected global economy, [3] foreign exchange rates have emerged as one of the major determinants of global trade. Consequently, various researchers have employed various techniques to predict currency exchange rates [4]. It's complicated to forecast currencies or anticipate future economic value. Because political and theoretical considerations have an impact on foreign exchange rates. Thus, a great deal of work has gone towards the examination and forecasting of the money market's future values [5]. The majority of countries currently have floating exchange rates, which are controlled by the foreign exchange market based on supply and demand for a given currency relative to other currencies. Central banks and other financial institutions also provide guidance on this system. The terms of trade, public debt, variations in inflation and interest rates, current-account deficits, political stability, and economic performance are a few of the variables that can directly or indirectly impact the exchange rate. Maintaining a close eye on this entire factor makes it challenging to predict exchange rates, volatility, and momentum more accurately. As a result, it is preferable to forecast the currency market using only data from the previous few years [7].

## 1.2 Motivation of the Research

With the foreign currency market being the most overhanging financial market worldwide, it has been understandable to predicting exchange rates is paramount for decision-makers, businesses, and investors. [6] The dynamics of exchange rates significantly influence global trade, making them a crucial determinant in the interconnected world economy. Exchange rate dynamics play an important part in shaping the interconnected global economy by expressing a considerable influence on global trade [8]. For financial institutions and businesses that deal with foreign exchange, forecasting exchange rates is crucial. Businesses that are exposed to this kind of risk must hedge their foreign exchange cash flows in order to safeguard their earnings from fluctuations in exchange rates. Hedging, however, is expensive and avoidable if accurate currency rate protection is achievable. Therefore, creating a research methodology based on predictions that is this effective would be very beneficial for banks and companies. Researchers have made a sincere effort to do this by creating a variety of models for predicting different currency exchange rates [9].

## 1.3 Problem Statement

Due to the complex interaction of variables including market outlook, international advancements, and economic data, accurately predicting foreign currency rates is extremely difficult [8]. Conventional approaches, such as technical and fundamental studies, are not very good at capturing the complex and dynamic patterns that are present in exchange rate fluctuations. The dynamic character of the worldwide economy imparts a degree of uncertainty [9], hence requiring strong forecasting techniques to effectively handle the complexities of the foreign exchange market. While useful, current models frequently come up short of providing an in-depth understanding of the interdependencies within the data. [10] A stronger and more reliable forecasting framework is clearly needed, especially as companies and decision-makers depend more and more on precise estimates to guide risk management and strategic financial planning [11]. In some of the research works, implementing a unique hybrid model called the ARIMA-Random Forest model, this research intends to fill in the gaps and overcome the obstacles that currently exist in foreign exchange rate prediction [13]. According to a survey on various ANN and ML types, the backpropagation algorithm is a popular learning method, but its rate of convergence is slow [14]. Neural network and fuzzy neuron models were employed in the application of machine learning models to predict the currencies traded in foreign exchange markets. It was discovered that the ARIMA model outperforms neural network and fuzzy neuron models in terms of predicting performance.[18] The lack of memory in the models of other neural networks is one of their drawbacks, which is particularly problematic for time series data. By producing both short-term and long-term memory components, LSTM solves this problem [20].

## 1.4 Research Questions

In the dynamic realm of foreign exchange markets, the accurate prediction of currency values is crucial for effective decision-making.[14] There are several approaches for effectively predicting currency exchange rates in the literature, such as time series models, models based on computer intelligence, and hybrid models.[17] This research aims to investigate the performance of a novel ARIMA-Random Forest hybrid model in forecasting foreign currency exchange rates. Thus, the final question focuses on examining the model's flexibility to different market situations, and the other questions continue to evaluate the effectiveness of the ARIMA-Random Forest combination model. To make our research more organized and ongoing, the following questions can be raised:

1. How does the combining ARIMA-Random Forest model at forecasting major currency exchange rates relative to the USD?

2. How does the suggested hybrid model offer into the reliability of its forecasting abilities and adjust to changing market conditions?

## 1.5 Research Objectives

To design and develop a model for predicting foreign currency exchange rate using ARIMA-Random Forest it fits well over the exchanging market condition over various currencies. Based on the literature, econometrics and machine learning models have garnered more attention in recent years for the analysis of exchange rate behavior [16]. Nevertheless, no single technique or set of techniques has shown the greatest results across all currencies. Furthermore, we discover that no model is able to outperform every other model for the exchange rate market in terms of several criteria. Forecasting remains one of the most difficult problems because of the intricacy of currency rates [18]. This research aims to propose a combined a hybrid model namely ARIMA-Random Forest model for accurately predicting foreign currency exchange rates. This study aims to evaluate how well the flexibility of Random Forest combined with ARIMA time series analysis may improve the accuracy of currency value projections also in the field of predicting currency exchange rates, combining Random Forest and ARIMA models promises high accuracy. The ultimate objective is to provide a trustworthy forecasting tool that is essential for firms who depend on currency rate projections to make well-informed decisions

[20]. In this article we have been used a time series based on EUR, AUD and CHF and GBP against USD forex data and developed ARIMA and Random Forest model and conducted a hybrid model by combining these two deep learning models into one and by evaluating the performance on the indicators RMSE, MSE and MAE. Also, we have found that this combined hybrid model performs effectively better and relatively consistently over the other existing model of different research works.

## 1.6 Research Scope

When it comes to predicting in the dynamic field of foreign exchange, the combination of Random Forest and ARIMA models offers a promising path to unmatched accuracy. This novel method seeks to strengthen our forecasts' ability to withstand changes in the dynamic world of global finance.[3] while also helping to understand the nuances of historical trends. This research thoroughly analyzes a variety of methods for forecasting foreign exchange rates, highlighting issues facing the sector today.[14] The evaluation includes traditional time series models, machine learning techniques, and hybrid approaches, taking into account significant variables such as market sentiment, geopolitical developments, and economic metrics.[18] Exchange rates are a key component of finance because they influence the decisions made by bankers, exporters, importers, and holders of foreign exchange. As a result, changes in exchange rates have a negative impact on an economy's capital flow and business cycle [19]. One special feature is the combination of Random Forest and Autoregressive Integrated Moving Average (ARIMA) models in a combined framework is to enable decision-makers to effectively navigate the highly unpredictable foreign exchange market with better prediction level accuracy. By doing this, we hope to contribute not only to precise forecasts [20] but also to the development of a strong framework that foresees and adjusts to the difficulties facing the financial markets of tomorrow.

# Chapter 2

# Literature review

This literature review investigates the usefulness of ARIMA and Random Forest models in predicting foreign exchange rates. By comparing different approaches, it hopes to uncover their respective strengths and limitations in forecasting currency changes, providing insights for better predictive accuracy in financial markets.

## 2.1 A Brief of Machine Learning Algorithms

Machine learning is based on multiple algorithms. Linear Regression, ARIMA, and SVM are some examples of supervised learning techniques that use labelled data to detect patterns-means clustering and PCA are two examples of unsupervised learning applied to unlabeled data to reveal hidden structures. Q-Learning and DQN are examples of reinforcement learning, in which agents must learn through trial and error while receiving rewards. In machine learning, decision trees with hierarchical splits such as Random Forest and Gradient Boosting allow for more efficient decisions. Random forests and gradient boosting machines are a few types of decision trees that use hierarchical splits. Neural networks such as CNN, RNN, and FNN are designed to imitate the architecture of the brain and can thus be utilized for tasks like sequence analysis and image processing. Combining several model’s ensemble methods, like as bagging and boosting, demonstrate the universality and adaptability inherent in machine learning as it attempts to address tough issues in a variety of disciplines.

### 2.1.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are a linkage structure that mimics biological neural networks with layers of nodes or neurons that process data. In ANNs, the input layer receives data and then passes it through hidden layers by use of weighted connections and activation functions so as to make it meaningful. The final output layer that makes predictions or classifications. Characteristics including weights, biases and other tunable parameters differentiate ANNs since they are changeable during training so as to enhance better performance. Non-linearity is introduced by activation functions such that more complex patterns can be learned by the network.

**Related Work**

Maneejuk et al. used artificial neural network technology to compute the annual profitability performance of each model for CHF/USD (percentage) between 2015 and 2017, as well as the average value, which was 27.0614%, 37.9118%, 42.7943%, 26.3475%, 18.9441%, and 30.6118%. Aydina and Cavdara use a VAR model to predict that these indicators will drop in different quarters, presenting alternative viewpoints on Turkey's impending economic disaster. In contrast, the ANN model anticipates large changes in the USD/TRY exchange rates as well as the BIST 100 index, indicating a probable financial hardship around October 2017.

### 2.1.2 Support Vector Machines (SVM)

Support Vector Machines (SVM) are highly effective supervised learning algorithms for classification and regression. These algorithms are able to identify the best hyperplane in feature space, which separates classes as much as possible while resulting in a maximal margin between data points from different classes. For instance, support vectors that close to the hyperplane define the decision boundary. The introduction of kernel functions allows SVMs to deal with both linear and nonlinear interactions.

SVMs can be applied to picture classification and text categorization among others due to their effectiveness with high-dimensional data. They work well even when there are outliers, focusing on the important ones among them. The high adaptability and efficiency of these machines place them in different fields where they can be used for complexly bounding complicated decisions.

**Related Work**

The study by Özorhan et al. uses a genetic algorithm to combine the flexibility and durability of SVM models to predict absolute currency strengths. Every day, the SVM parameters are fine-tuned to perfection using a variety of applications, such as defect classification and stock price predictions. When evaluating a varied range of six main currency pairs, the technique attained an accuracy of 78.78%, which was higher than the 62.38% achieved by algorithms focused on particular currency pairs.

### 2.1.3 Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) is a fundamental time series prediction model that combines components of auto regression, differencing, and moving average. Although the basic ideas remain unchanged there could be subsequent works trying to better parameterize the model, find better ways to handle non-stationarity problems and introduce machine-learning tools to improve accuracy of forecasts. The autoregressive part models the relationship with previous observations whereas differencing ensures stationarity by altering a time series. The moving average component looks at how current observation is related with the residual errors of a lagged moving average model.

In application of late, academicians and practitioners may go for hybrid models which combine ARIMA with other forecasting approaches thus taking advantage of each one's strengths. Tweaking techniques and adding novel insights might make the model more flexible across time-series data sets. Although ARIMA continues to be an appropriate choice but staying updated with latest literature and resources helps ensure that practitioners are using the most recent methods or insights in time series forecasting.

**Related Work**

Panda et al. [Panda et al., 2021] uses a convolutional neural network-based strategy that takes advantage of multivariate data, can estimate multiple currency exchange rates with more precision than classic techniques such as ARIMA and linear regression. This is especially true for short-term forecasts. In foreign exchange rate predictions, the CNN-Random Forest model outperformed the MLP, ARIMA, and Linear Regression models. The MAPE ranges for AUD/USD, EUR/USD, USD/CAD, and GBP/USD are 71.42% to 88.88%, 86.20% to 91.33%, 84.81% to 85.88%, and 84.61% to 86.66%, respectively, indicating variances between these models.

### 2.1.4 Random Forest Regression (RFR)

Random Forest Regression is an ML (machine learning) algorithm that integrates different decision trees together to create predictive models. A "forest" is built by training several trees using various subsets of the given dataset. Every tree predicts the target variable on its own, and the prediction of a full model consists in either their weighted sum or average. This way of dealing with many models increases accuracy, robustness, and reduces overfitting as well. Random Forest Regression is ideal for complex relationships between variables in regression tasks such as finance, healthcare, environmental sciences and so on because it can be used to predict continuous outcomes for multiple topics (in financial services).

**Related Work**

Panda et al. In foreign exchange rate predictions, the CNN-Random Forest model outperformed the MLP, ARIMA, and Linear Regression models. The MAPE ranges for AUD/USD, EUR/USD, USD/CAD, and GBP/USD are 71.42% to 88.88%, 86.20% to 91.33%, 84.81% to 85.88%, and 84.61% to 86.66%, respectively, indicating variances between these models. Rabbi et al. calculated the performance algorithm utilizing MAE, MSE, RMSE, and MAPE for twenty-two currencies, including the Australian dollar, Euro, New Zealand dollar, and United Kingdom pound, against the USD dollar, and found that the Random Forest Regression (RER) model outperformed the other models.

### 2.1.5 Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM), a specialized recurrent neural network (RNN), is good at tasks that involve sequences and solves the problem of vanishing gradient. LSTMs, which capture long-term dependencies using memory cells and gating mechanisms, are widely used in natural language processing and time series forecasting. However, subsequent advancements might focus on hyperparameter tuning, exploring changes like Gated Recurrent Units (GRUs) or FPGA and combining LSTMs with attention mechanisms or transformer architectures. Staying abreast of these developments allows users to fully leverage the potential of LSTMs for dealing with difficult sequential data problems.

**Related Work**

Lu [Lu, 2022] GBP/CNY Forex statistics from January Lu [Lu, 2022] GBP/CNY FX data from January 2020 to September 2021 were analyzed using ARIMA, LSTM, and GRU algorithms. LSTM stood out for its forecasting accuracy. The study also discovered that superconducting components had varying effects on the LSTM and GRU approaches, while the ARIMA methodology yielded consistent results. The LSTM model outperformed the ARIMA model. It decreased the RMSE, MAE, and MAPE errors by 2.28%, 7.48%, and 23.69%, respectively. This shows that all errors were less serious. Additionally, the LSTM model improved its ability to predict GBP/CNY exchange rates. It reduced the RMSE by 16.42%, MAE by 24.26%, and MAPE by 23.69% when compared to the GRU model. Maneejuk et al. [Maneejuk et al.,2021] describe the foreign exchange market rate of five different currencies (JPY, GBP, EUR, CHF, and CAD) over the USD change rate using different ML models and demonstrate that the long short-term memory (LSTM) model outperforms the others on average. The average of LSTM has been forecasted in EUR/USD, GBP/USD, CAD/USD, JPY/USD, and CHF/USD, correspondingly, and September 2021 annual.

## 2.2 Summary

Predicting Foreign Currency Rates (FCR) requires the use of several statistical and machine learning methods. Artificial Neural Networks (ANN) models the learning process of the human brain, which adapt to complex patterns in past currency data. Support Vector Machines (SVM) use the discovery of hyperplanes that divide classes to perform efficient classification and trend prediction. Understanding the structure of currency rates can be aided by using Autoregressive Integrated Moving Average (ARIMA), which effectively captures seasonality and linear patterns in time-series data. Recurrent neural networks such as Long Short-Term Memory (LSTM) are particularly useful for deciphering intricate patterns or hidden links in historical data. Because of its capacity to handle heterogeneous data, Random Forest Regression (RFR) has emerged as one of the most well-known ensemble learning techniques. This is because RFR is robust for FCR prediction. It generates a large number of decision trees and combines their output to offer precision and robustness.

In summary, every model has advantages of its own. While SVM excels at trending classification, ANN and LSTM are adept at identifying complex patterns, ARIMA captures time-dependency structures, and Random Forest efficiently mixes decision trees. Several factors, including data set features, interpretability requirements, and forex market dynamics, will influence the optimum model selection. The Random Forest Regression model appears to be a powerful and accurate tool that can handle a variety of variables. The ensemble technique makes even-handed predictions, making it one of the better models under consideration. When selecting the optimal model for predicting foreign currency rates, it is important to consider specific situations and contextual factors that reflect the evolving field of predictive analytics.

# Chapter 3

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# Methodology

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This section explains the concepts and methods used to model daily exchange rate data. The exchange rate data collected from the Kaggle under consideration is from December 2003 to August 2022 and comprises various observations. Stochastic functions called forecasting equations are used to predict a phenomenon's unusual behavior, assisting in the making of decisions. To understand this behavior, we use historical data, i.e., the variable's Y t-1 lag, and forecast the Y t current value. As stated in Equation, the procedure is used to identify a mathematical function F that sufficiently draws the inputs and yields the intended output result.

$$\hat{y}\, t = F\,(y\, t\, 1, y\, t\, 2, \ldots.\;, y\, t\, k\,) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\;(eq{:}\,1)$$

It is noteworthy that the function F can be analyzed using either a linear or non-linear methodology. This research makes use of Autoregressive Integrated Moving Average (ARIMA) which is linear and non-linear. Then use the non-linear model Random Forest model. After predicting the single model then we create a hybrid model that works with ARIMA and Random Forest. This model first works with ARIMA whose value can't be predicted by ARIMA then works with Random Forest rest of the value in the dataset.

## 3.1 Dataset

The title of this dataset is **"Currency Exchange Rates"** available on **Kaggle** and this dataset was compiled by **Dhruvil Dave.** Here likely contains information about exchange rates between different currencies. Numerous currency pairs, including USD/EUR, USD/GBP, USD/JPY, etc., are included in this dataset. This dataset's pairs each show the exchange rate between two different currencies. We use the close column as our target variable. This section displays historical exchange rate data, which usually consists of daily or hourly rates for a given time frame. We may examine patterns, trends, and oscillations in currency exchange rates over time with the help of this data. The dataset probably contains timestamps or date-and-time data associated with every exchange rate observation.

All make it possible to analyze data over time and spot periodic or seasonal patterns in currency markets. The rate at which one currency can be exchanged for another is indicated by an exchange rate, which is expressed as a numerical value. Different forms, such as direct rates, for instance, 1 USD = 0.85 EUR and indirect rates one euro = 1.0.18 USD may be used to present these numbers.

We are reliant on the dataset's origin and entirety; it might include additional data like the amount of money exchanged, opening and closing rates, high and low rates for each period, and any pertinent metadata. Evaluating the data's quality and consistency, taking into account any missing numbers, outliers, or discrepancies, is crucial. This might always affect how exchange rate developments are analyzed and understood.

## 3.2 Procedures

**Data Preparation**

The time series graphic can be examined to find trends, outliers, and seasonality. Examine the absent values to comprehend their distribution. examining the mean, standard deviation, and quartiles, among other important statistics. when we choose a method, such as interpolation, removal, or forward/backward filling, to deal with missing values: We have to make sure that the time series are not biased by the imputation techniques. We can use statistical methods or visualization techniques to find and analyze outliers. if it is thought suitable, eliminating extreme values or taking into account the finest methods. Make sure the time series is stationary, or adjust it so that it becomes stationary. Logarithmic transformations and differencing are common methods. To identify past trends in the data, we can create lag features. Moreover, we can experiment with different lag values according to the domain expertise and the properties of the data. When working with time series data, divide the dataset into time-ordered segments to better represent actual situations. We can A specific portion of the data should be used for testing, and the remainder for training. To prevent data leaking, we take into consideration time series cross-validation approaches for model evaluation. Since the data is not steady, we use differencing to make it so for our experiment, varying the differencing orders to determine the best value. Next, we must make sure that the features and target variables in our final dataset are ordered correctly and have the required structure for model training. We then plot the preprocessed time after that. Next, we visually verify that the trends.

## Model Architecture

### Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive (AR) and Moving Average (MA) models are combined in this methodology. When the time series variables are univariate, these models predominate and are effective at predicting the future values of the time-series data. Using the moving average component (MA) of the model and the autoregressive component (AR) to examine the series dependent on the past, this model seeks to capture the autocorrelation pattern. We create a correlogram of the data and indicate the sequence in which to estimate the model for the underlying phenomena to determine both parts. When the data is non-stationary, this model is commonly applied; if the data is stationary, any portion of it can be used appropriately. This model can be expressed mathematically as

$$yt = \varphi 0 + \varphi 1yt\ 1 + \varphi pyt\ p + \theta 1\varepsilon t\ 1 + \theta\ q\varepsilon t\ q\ + \mu \ldots \ldots \ldots \ldots \ldots \ldots (eq{:}\ 3.2)$$

### Random Forest Regression (RFR)

One machine learning method for regression tasks is random forest regression. Using randomly chosen subsets of the training data and features, a random forest model builds a large number of decision trees. The consensus prediction, which is typically more accurate than any single tree, is created by combining the individual trees. This method also lessens overfitting, a common issue in machine learning where a model performs poorly on new data because it is too closely tailored to the training set. Random forests are more adaptable and can represent nonlinear relationships between variables than linear regression, which is a straightforward and understandable technique for modeling linear relationships between variables. Random forests can also recognize significant features for prediction and handle a large number of features. All things considered, random forests are an effective and user-friendly machine learning tool, even for people with no prior experience with the field.

**Data Transformation**

Data transformation is another important part of preparing time series data for ARIMA and Random Forest models. Here we discuss how to perform data transformations:

First, we apply differencing to make the time series stationary. Then experiment with differencing with orders until stationarity is achieved. Random Forest models are less sensitive to non-stationary data, so stationarity may not be a strict requirement. If we need to consider applying differencing or transformations based on the nature of your dataset. The Random Forest model is not inherently sensitive to feature scaling, but scaling may benefit certain algorithms or improve convergence. Scale the features using Min-Max Scaling or Standard Scaling. After this, if we need a dataset that includes categorical features, encode them appropriately. For Random Forest, we can use a one-hot encoding.

**Model Training**

For training our model follows some steps. Now describe this in below:

**Data Preparation:**

For preparing our time series data, addressing issues like missing values, and outliers, and ensuring the dataset is suitable for time series analysis. Perform any necessary transformations, such as differencing to achieve stationarity, creating lag features, and encoding categorical variables.

**Splitting the Dataset:**

Split the preprocessed dataset into training and testing sets. Since time series forecasting is inherently temporal, use a time-based split to ensure that the model is evaluated on unseen future data.

**Arima Model Training:**

When we train the ARIMA model on the training set. ARIMA absorbs the temporal patterns and dependencies within the time series data. Then we specify the order of differencing and autoregressive and moving average parameters based on the prior analysis and domain knowledge.

### Random Forest Model Training:

For Train a Random Forest model on the training set, Random Forest is capable of capturing complex, non-linear relationships in the data. We use lag features, possibly incorporating the ARIMA residuals, as input features for the Random Forest model.

### Proposed Model:

Combine the predictions from both models to create a hybrid forecast. This can be achieved by averaging the predictions or using a weighted average. The idea is to leverage the strengths of both models, with the hope that any weaknesses in one model are compensated by the strengths of the other.

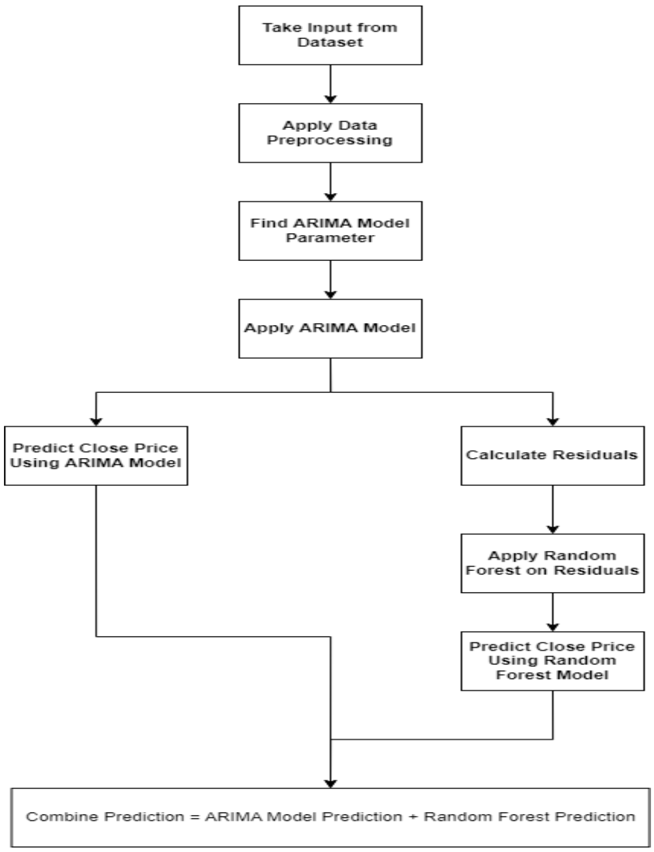


***Figure 3.1 :*** *Proposed Model Architecture*

**Key performance indicator (KPI)**

Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE) are a few of the criteria used to compare performance and select the optimal approach among the underlying algorithms. In this work, the model's performance is assessed using each of these criteria. In statistical models, the MSE quantifies the coefficient of error terms. It evaluates the mean square of the discrepancies between the observed and anticipated data points. The MSE is equal to zero when the error term has a zero value, and the MSE's root is referred to as the mean error between the predicted and observed values is computed using RMSE and MAE. Finally, the absolute mean percentage error for the data is measured using the MAPE. These models can be expressed mathematically as equations.

$$MSE = 1\ Ns \sum Ns\ n = 1\ (dn\ yn)2 \qquad \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (eq: 3.3)$$

$$MAE = 1\ Ns \sum Ns\ n = 1\ |dn\ yn| \qquad \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. (eq: 3.4)$$

$$MAPE = 100\ Ns \sum Ns\ n = 1 \ \Big| \Big| \Big| \Big| \ dn\ yn\ dn \ \Big| \Big| \Big| \qquad \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (eq: 3.5)$$

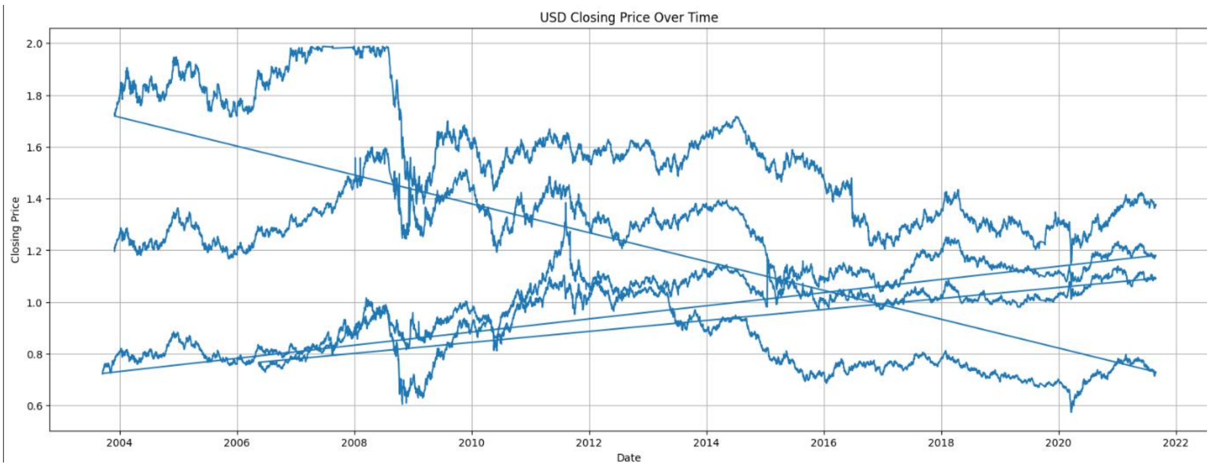


*Figure 3.2: Graphical display of the daily Exchange Rate data set.*

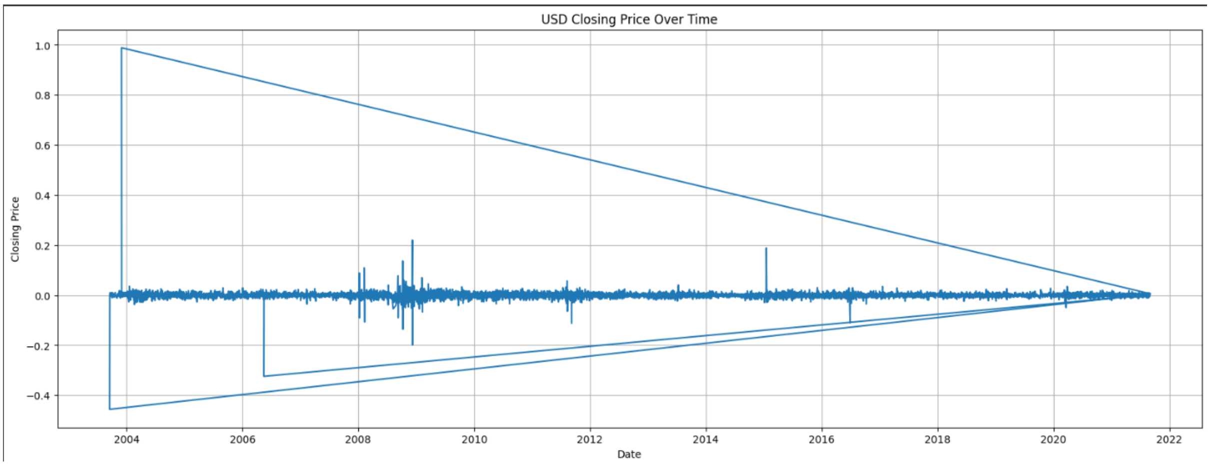


***Figure .3.3:*** *Check the stationary.*

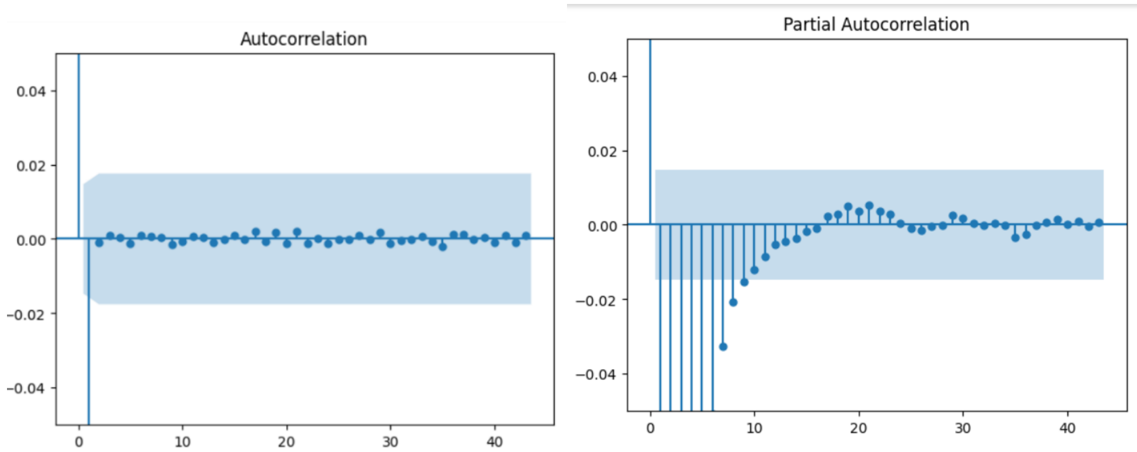


***Figure 3.4:*** *Check P & Q value.*

### 3.3.5 Validation Methodology

Evaluating the hybrid Random Forest and ARIMA model's predictive accuracy and dependability in predicting foreign exchange rates is the goal of validation. To comprehend a thorough dataset of past foreign exchange values over an appropriate time frame. The dataset was divided into testing and training sets. The test set will be saved for the last assessment, and the validation set dataset will be utilized to adjust model hyperparameters. Common assessment metrics such as R-squared (R2), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used to analyze the performance and validity of a combined model. From our work we get this value RSME: **0.00584**, MSE:**0.00003** MAE: **0.00466.** This value is so much better than others. If we look at other results generated by a single Arima model- RMSE - 2.28%, MAE - 7.48%, MAPE - 23.69% and single random Forest Model-71.42% to 88.88%, 86.20% to 91.33%, 84.81% to 85.88%, and 84.61% to 86.66%. Here we see the single model doesn't generate a satisfactory result. But combined prediction we get a better result. In single model prediction, we can't get the result of the whole dataset because each model works in a specific part of the dataset but when we create a combined model, we get the result whole dataset. Which data isn't predicted by a single model this one is predicted by another model. Our model works so much excellently in statistical data and we predict linear and non-linear both types of data. We added some additional features to our dataset to get results properly, which makes our dataset more perfect.

The strength of the Arima and Random Forest combined model the accuracy of the prediction is much better than a single prediction and it predicts the linear and non-linear type of data which work is not possible by a single model.

# Chapter 4

# Result and Findings

The main focus of this study is to forecast exchange rates between EUR/USD, GBP/USD, CHF/USD, and AUD/USD currency pairs. To accomplish this mission, we developed a sophisticated hybrid model that combines ARIMA and random forest techniques. This section thoroughly examines and verifies the performance effectiveness of our model.

## 4.1 Model Evaluation

The dataset, which included daily observations of 17,782. This involved a detailed missing values analysis, confirming data integrity as well as correlation features that showed strong interrelationships between the variables.

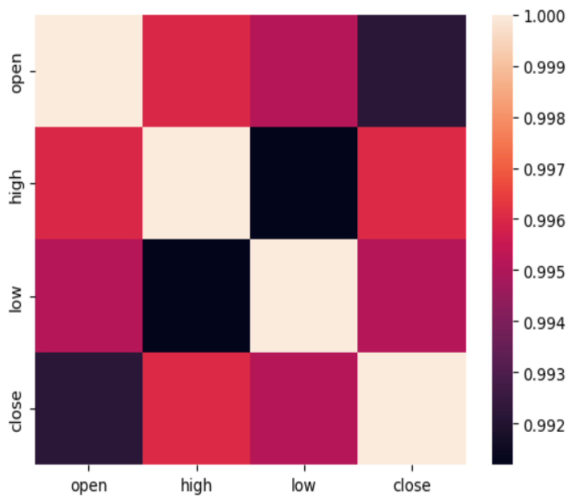


***Figure 4.1:*** *Observe the correlation features*

After the improvement of data quality through outlier detection, it paved the way for complex modeling and feature engineering.

### 4.1.1 ARIMA Model Evaluation

The residual distribution for the ARIMA(0,1,0) model fitted from differenced variables proved to be normal. The performance measurement indicated a good fit of the model as Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) showed to be 0.00550, 0.00003, and 0.00454, respectively. The linear dependencies in the data were captured effectively by the ARIMA model's ability to withstand other factors.

### 4.1.2 Random Forest Model Evaluation

The random forest model's capability to handle complexity beyond the limitations of traditional ARIMA models was also seen in terms of residuals.

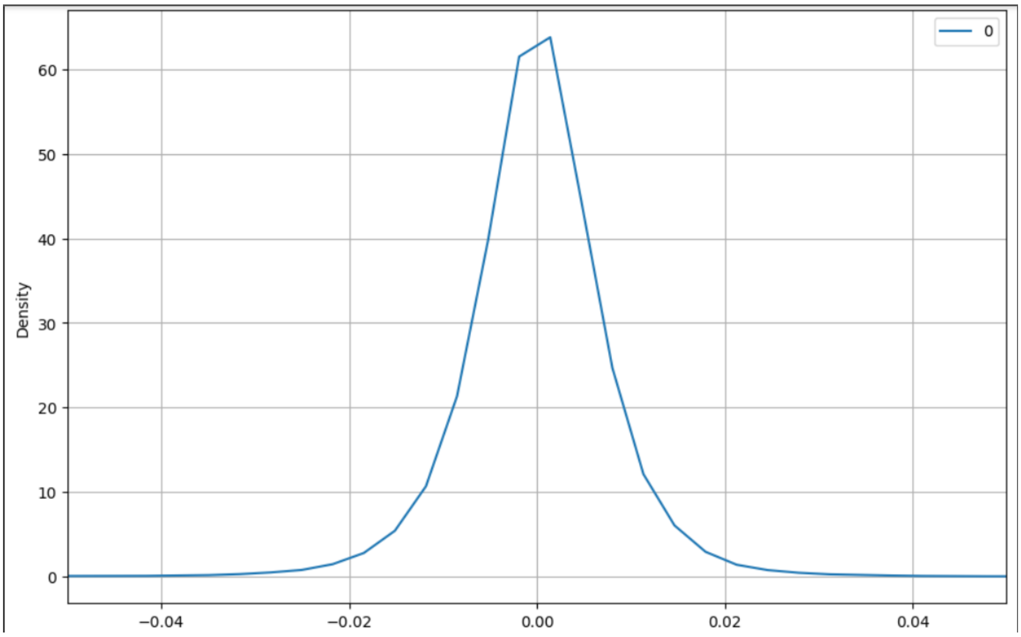


*Figure 4.2: Graphical display of calculated residuals*

Performance metrics were RMSE at 0.00656, MSE at 0.00004, and MAE at 0.00515 of the above shown to be doing well for the model in spotting hidden patterns on the residuals especially those with nonlinear dynamics.

## 4.2 Model Validation

However, although the performance statistics of ARIMA and Random Forest models were praiseworthy individuals, the hybrid model aimed at consolidating their merits. The integration of the ARIMA and Random Forest models led to synergetic benefits, mainly improving forecasting in general. The hybrid model had a compound RMSE of 0.00584, MSE of 0.00003, and MAE of 0.00466 in totality Visual comparisons demonstrated the effectiveness of the hybrid model, close to true currency fluctuations.

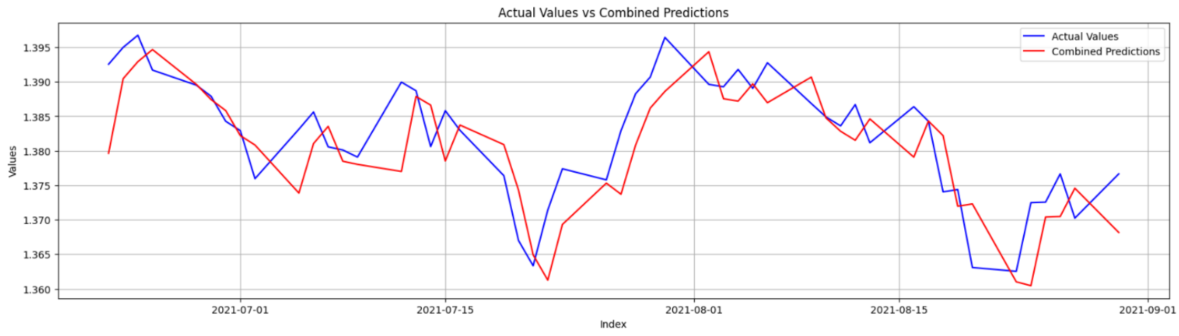


***Figure 4.3:*** *Observe the actual values vs predicted values fluctuations*

This fusion demonstrated the ability of this model to successfully find not only linear dependencies but also nonlinear dynamics within the dataset.

## 4.3 Comparison Table

| Paper | Dataset | Model | Performance |
|---|---|---|---|
| Proposed Model | Currency Foreign Exchange Rates (Modified) | ARIMA and Random Forest | RMSE - 0.00584, MSE - 0.00003, MAE - 0.00466 |
| Lu, Changhui | GBP/CNY exchange rate. | ARIMA, LSTM and GRU Model | RMSE - 2.28%, MAE - 7.48%, MAPE - 23.69%. |
| Nayak et al. | JPY/INR currency on a daily basis. | LSTM-KNN model. | RMSE - 0.0057 to 0.3919 |
| Wei et al. | Foreign exchange rates are EUR/USD, USD/CNY, and USD/JPY. | Variational mode decomposition (VMD), the self–organizing map (SOM) network, and the kernel extreme learning machine (KELM). | MAPE – 20.77% |
| Qureshi et al. | The real exchange rate data set (REER). | MLP, ELM, ARIMA, EST Model. | MSE - 20.38% |
| Yong et al | The historical currency exchange price of the three major currency pairs dataset. | GMMINF, ALMMo | RMSE - 0.0060%, MAPE - 0.3573% |
| Kartono et al. | The economic variables affecting the exchange rate data | NLSE, Black-Scholes Model, The numerical method | MAPE - 0.48% |
| Asadullah et al. | Pakistani Rupee's Exchange rate against the United States Dollars Dataset | NARDL, ARIMA, Naïve, Exponential smoothing | MAPE - 0.612 |

**Table 4.1:** Comparison Table

# Chapter 5

# Conclusion

## 5.1 Findings and Contribution

In conclusion in, this study aims to address the complex environment of the foreign exchange market, which is defined by the dynamic interaction of market, political, and economic factors. Understanding how difficult it would be to predict currency prices amid these complications, our research suggests a unique solution: the ARIMA-Random Forest hybrid model. In combination with ARIMA's proficiency in time-series analysis, this combination utilizes Random Forest's ability to detect complex patterns. The hybrid model was useful in predicting exchange rates for important currency pairings, such as EUR/USD, GBP/USD, CHF/USD, and AUD/USD, during the period of our analysis. The accuracy and prediction rate results show an exceptional performance over our model, suggesting the greater accuracy of this model over the existing ones.

In summary, the hybrid model of ARIMA and Random Forest demonstrates significant potential in offering organizations a dependable tool for generating educated selections grounded in precise currency rate forecasts. This study acknowledges current accomplishments and establishes a way for a changing and flexible future in foreign exchange rate forecasting as we navigate the complexity of the financial world.

## 5.2 Recommendations for Future Work

We are eager to work over another currency rate for a larger audience should be the main priority to increase user engagement and applicability. Furthermore, the identification and integration of novel elements into the model along with the comparison with existing models will enhance its flexibility and guarantee consistent performance in a range of market scenarios. Because the financial sectors are dynamic, there must be a constant dedication to development and a continuing attempt to modify the model in response to changing market patterns. Our model, while promising, requires ongoing development to address specific areas. Enhancing interpretability is marked as a key priority, making the model more accessible and understandable for users. Identifying additional features and ensuring stability across diverse market conditions are vital considerations. Maintaining accuracy and flexibility requires a persistent dedication to development, especially given the dynamic nature of the financial sectors.

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