USD-INR Exchange Rate Prediction Using ARIMA-GARCH Models

Introduction:

The USD – INR conversion rate stands as a pivotal economic indicator with far-reaching implications for both India and the United States, significantly influencing sectors such as import-export business, foreign investment, and tourism, among others. The dynamic nature of currency exchange rates necessitates a thorough understanding of historical trends and a forward-looking approach to forecasting. In this context, the present project assumes significance, as it endeavours to analyse historical data and predict future USD-INR exchange rates. By harnessing advanced time series modelling techniques, the project aims to provide stakeholders with invaluable insights. These insights not only facilitate risk mitigation but also empower decision-makers to optimize currency conversions and strategically plan financial initiatives. In an ever-evolving global economic landscape, the ability to anticipate and adapt to changes in the USD-INR conversion rate becomes a strategic advantage for individuals and institutions alike.

Objective:

The major goal of this project is to use time series analysis to create a strong and reliable forecasting model for predicting the exchange rate between the US dollar (USD) and the Indian rupee (INR). To capture both the trend and volatility in currency exchange rates, a mix of Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models will be used.

Methodology:

1. Data Collection

Historical weekly USD-INR exchange rate data is collected from reliable financial sources. The dataset contains the value of INR for 1 USD for a given time. Below are all the features in the data:

1. Date: The date represents the specific day of the exchange rate data.
2. Open: The opening price refers to the exchange rate at the start of a specific trading period, such as the opening price for the day or the week. It represents the initial value at which the USD-INR conversion rate was traded.
3. High: The high price represents the highest exchange rate observed during a specific trading period. It means the maximum value reached by the USD-INR conversion rate during this period.
4. Low: The low price represents the lowest exchange rate observed during a specific trading period. It indicates the minimum value reached by the USD-INR conversion rate during this period.
5. Closing: The closing price represents the exchange rate at the end of a specific trading period, such as the closing price for the day or the week. It shows the final value at which the USD-INR conversion rate was traded.
6. Adjusted Closing: The Adjusted Closing Price considers any corporate actions, such as stock splits or dividends, that may affect the Closing Price. In the context of USD-INR conversions, this feature could represent an adjusted closing exchange rate.

7. Volume: Volume refers to the total number of USD-INR currency pairs traded during a specific trading period. It quantifies market activity and liquidity for the given exchange rate.

2. Data Pre-processing:

In the data pre-processing phase of this project, a focused approach was taken to streamline the dataset for effective time series analysis. The decision was made to retain only the Adjusted Close price as the key variable for predicting USD-INR exchange rates. The Adjusted Close price, accounting for corporate actions that might influence the Closing Price, emerged as the most pertinent metric for capturing the intrinsic value of the currency pair at the end of each trading period. By discarding redundant columns such as Open, High, Low, Closing, Volume, and Date, the dataset was refined to enhance model efficiency and reduce computational complexity.

Addressing the challenge of missing values in the Adjusted Close column, a pragmatic solution was implemented using the backward filling methodology. This technique involves replacing missing values with the most recent observed value, thereby ensuring a continuous and coherent time series. This approach is particularly suitable for financial data where the temporal order of observations is critical. By carefully curating the dataset and employing a robust imputation strategy, the project ensures that the subsequent ARIMA-GARCH model is built upon a solid foundation, allowing for accurate and reliable predictions of USD-INR exchange rates.

3. Exploratory Data Analysis (EDA):

During the Exploratory Data Analysis (EDA) phase, pivotal insights were gleaned through rigorous statistical tests and decomposition techniques.

1. The application of the Dickey-Fuller test revealed that the initial USD-INR exchange rate data was non-stationary, indicating the presence of a discernible trend.
2. Further decomposition of the time series uncovered a recurring periodicity, with a clear weekly cycle observed in the dataset. Leveraging this knowledge, a seasonality period of 52 weeks was identified, aligning with the weekly interval of data collection.
3. Moreover, the examination of squared residuals from the decomposition underscored the existence of volatility within the dataset. This volatility, indicative of fluctuations in exchange rate values, became a crucial consideration for robust modelling.

The decision to incorporate Seasonal Autoregressive Integrated Moving Average (SARIMA) was motivated by the detected trend and seasonality, which allows for a more accurate portrayal of the underlying patterns in the USD-INR exchange rates. Recognizing the presence of volatility, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model should be appropriately implemented to successfully describe the variance of the time series, boosting the overall model's predictive capabilities. These detailed findings from the EDA phase not only influenced the modelling methodologies chosen, but also highlighted the importance of addressing both trend and volatility components in USD-INR exchange rate projections

4. Model Construction:

ARIMA Model:

Following a thorough examination of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, a strategic choice was made to fit the USD-INR exchange rate data to a Seasonal Autoregressive Integrated Moving Average (SARIMA) model with parameters $(2,1,0)x(2,1,0)_{52}$. The ACF and PACF graphs gave useful insights into the autocorrelation structure, influencing the SARIMA model parameters choosing. To adequately capture the underlying trends in the weekly exchange rate data, the chosen SARIMA model takes into consideration a seasonal differencing order of 1 and employs autoregressive and moving average components.

GARCH Model:

Following that, recognizing the significance of addressing volatility in the SARIMA model residuals, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was fitted. This sequential approach guarantees a thorough modelling strategy by accounting for residual variability through the GARCH framework as well as addressing temporal dependencies and seasonality in the data. The combined SARIMA-GARCH model is positioned to provide a strong and accurate prediction of USD-INR exchange rates, combining the characteristics of both models to improve forecasting capabilities overall. This dual-modelling paradigm emphasizes a complex approach to time series analysis, recognizing both trend and volatility components for a more comprehensive forecasting framework

5. Model Evaluation:

The modelling process was conducted on a training dataset encompassing the initial 80% of the observations, ensuring a robust foundation for the SARIMA-GARCH framework. Following the model fitting, a rigorous validation was performed by predicting the observations within the testing dataset, representing the remaining 20% of the data. The predictive accuracy of the model was evaluated using key performance metrics.

The results of the validation phase revealed a Mean Squared Error (MSE) of 12.9288, indicating the average squared difference between the predicted and actual values. The Mean Absolute Error (MAE) was computed at 2.9941, representing the average absolute difference between the predicted and actual values. Additionally, the Mean Absolute Percentage Error (MAPE) was determined to be 0.0394, signifying the average percentage difference between the predicted and actual values relative to the actual values.

These metrics collectively provide a comprehensive assessment of the model's accuracy and effectiveness in predicting USD-INR exchange rates. The low values of MSE, MAE, and MAPE suggest that the SARIMA-GARCH model performs well in capturing the underlying patterns and variability in the data, demonstrating its reliability in forecasting exchange rates. These outcomes underscore the model's utility in making informed decisions and predictions within the dynamic landscape of currency exchange markets.

Conclusion:

Finally, this study effectively tackled the difficult challenge of projecting USD-INR exchange rates by employing a complex time series modelling approach. The comprehensive methodology included extensive data preparation, using only the Adjusted Close price, and resolving missing values using a backward filling mechanism. The Exploratory Data Analysis (EDA) phase revealed critical insights, such as the data's non-stationarity, repeated weekly seasonality, and the presence of volatility, which guided the selection of relevant models.

The decision to employ a SARIMA(2,1,0)x$(2,1,0)_{52}$ model was informed by a careful examination of ACF and PACF plots, allowing for the effective capture of both trend and seasonality. Subsequently, the integration of a GARCH model on the residuals further enhanced the predictive capabilities, accounting for volatility and ensuring a comprehensive modelling strategy.

The model's performance was rigorously validated using a testing dataset, and the results, with a Mean Squared Error (MSE) of 12.9288, Mean Absolute Error (MAE) of 2.9941, and Mean Absolute Percentage Error (MAPE) of 0.0394, demonstrated its accuracy in forecasting USD-INR exchange rates. These metrics indicate that the SARIMA-GARCH model excels in capturing the intricacies of the underlying data, providing a reliable tool for stakeholders in the financial markets.

This study adds important insights to the field of financial forecasting by providing users with a robust tool for navigating the volatile terrain of currency exchange rates. The successful application of the SARIMA-GARCH model demonstrates the project's ability to make accurate predictions, mitigate risks, and optimize investment strategies in the ever-changing world of international financial markets.