Currency Rates Predictions

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BACKGROUND

Currency exchange rates stand as a critical barometer in the world economy, shaping the dynamics of international trade, affecting import and export values, and influencing everything from individual purchasing power to the macroeconomic stability of nations. These rates, representing how much of one currency can be exchanged for another, are affected by many factors, including geopolitical events, economic policies, inflation rates, and overall market sentiment.

The ability to forecast currency exchange rates is invaluable for several sectors. For corporations engaged in international business, accurately predicting these rates helps in strategic budgeting and pricing, allowing them to mitigate risks associated with currency fluctuations. Financial institutions and investors rely on these forecasts to make informed currency trading, hedging strategies, and portfolio diversification decisions. Governments and monetary authorities utilize these predictions to tailor fiscal and monetary policies to stabilize the economy and control inflation.

In essence, the precision of currency rate forecasting has far-reaching implications. It serves as a crucial tool for economic planning and decision-making at various levels and contributes to the overall health and predictability of the global financial system. The complexity and interconnectivity of factors influencing exchange rates make this forecasting a challenging yet essential endeavor in international finance.

OBJECTIVE

To predict and forecast the closing exchange rate of currencies of the top global economies against US Dollar (USD). The different currencies in consideration are British Pound (GBP), Chinese Yuan (CNY), Euro (EUR), Indian Rupee (INR), Japanese Yen (JPY). Here we perform a Time Series Analysis for the currencies as mentioned earlier and build a Prophet model to forecast their exchange rates 7 days into the future.

APPROACH

PART 1: Data Extraction

We aggregated the historical exchange rate data for the aforementioned group of currency pairs against the USD, utilizing the Yahoo Finance API, which can be easily accessed through a python package. We compiled data for the Euro (EUR), Japanese Yen (JPY), British Pound (GBP), Chinese Yuan (CNY), and Indian Rupee (INR) from the beginning of 2000 to the current date. The dataset contains several useful columns like information on a very granular level (daily information). This dataset gets updated on a daily frequency except for weekends and holidays when the respective national exchanges are closed. A snippet of the dataset is as follows:

Date	Open	High	Low	Close	Adj Close	Volume	Currency_Pair
2003-12-01 0:00	1.203398347	1.20400691	1.194400668	1.196501374	1.196501374	0	EURUSD=X
2003-12-02 0:00	1.196100712	1.210903049	1.194600344	1.208897471	1.208897471	0	EURUSD=X
2003-12-03 0:00	1.208999753	1.213003397	1.207700372	1.212297559	1.212297559	0	EURUSD=X
2003-12-04 0:00	1.212003708	1.214402795	1.204398394	1.208094239	1.208094239	0	EURUSD=X
2003-12-05 0:00	1.207802415	1.219095945	1.206592798	1.218694687	1.218694687	0	EURUSD=X
2003-12-08 0:00	1.216796756	1.224005222	1.215406537	1.222000957	1.222000957	0	EURUSD=X
2003-12-09 0:00	1.222105384	1.227701783	1.219794869	1.224994779	1.224994779	0	EURUSD=X
2003-12-10 0:00	1.224904776	1.226602554	1.216204762	1.219095945	1.219095945	0	EURUSD=X
2003-12-11 0:00	1.219095945	1.22349596	1.212297559	1.222404242	1.222404242	0	EURUSD=X

The metadata is as follows:

Date: Represents the specific day for which the currency data is recorded.
Open: Refers to the opening price of the currency pair on the given date
High: Indicates the highest traded price of the currency pair during the day's trading session.
Low: Denotes the lowest traded price of the currency pair throughout the trading session on that date.
Close: Represents the closing price of the currency pair for the trading session
Currency_Pair: EURUSD=X (1 EUR = X USD), GBPUSD=X (1 GBP = X USD),
INR=X (1 USD = X INR), JPY=X (1 USD = X JPY), CNY=X (1 USD = X CNY)

PART 2: Data Preprocessing and Analysis

Initially, we dropped the unnecessary and redundant columns with no relevance in prediction, like the "Volume" column and the "Adj. Close" column.

We checked for all the null values and removed them. While there were no significant outliers in the data except for JPY, we checked and removed all the outliers. As financial data tends to be precise (up to 10-12 decimal places), we formatted the numerical data to contain information up to three decimal places. This preprocessing helps model efficiency and eliminates calculations.

After the initial preprocessing steps, the plots of the data look like this:

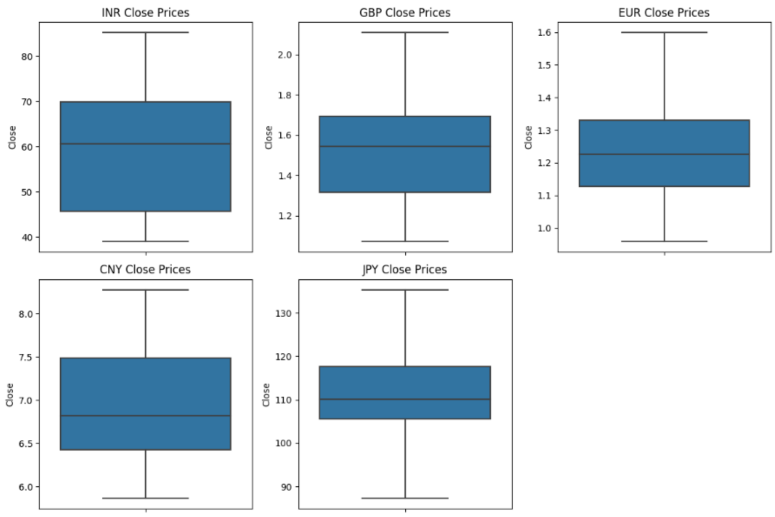

Fig.1: Box plot of the distribution of closing price values for different currencies.

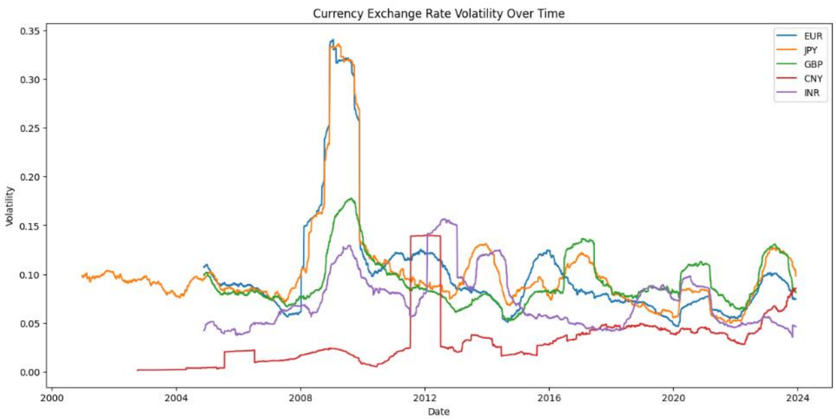

Fig.1: Volatility of Currencies across time

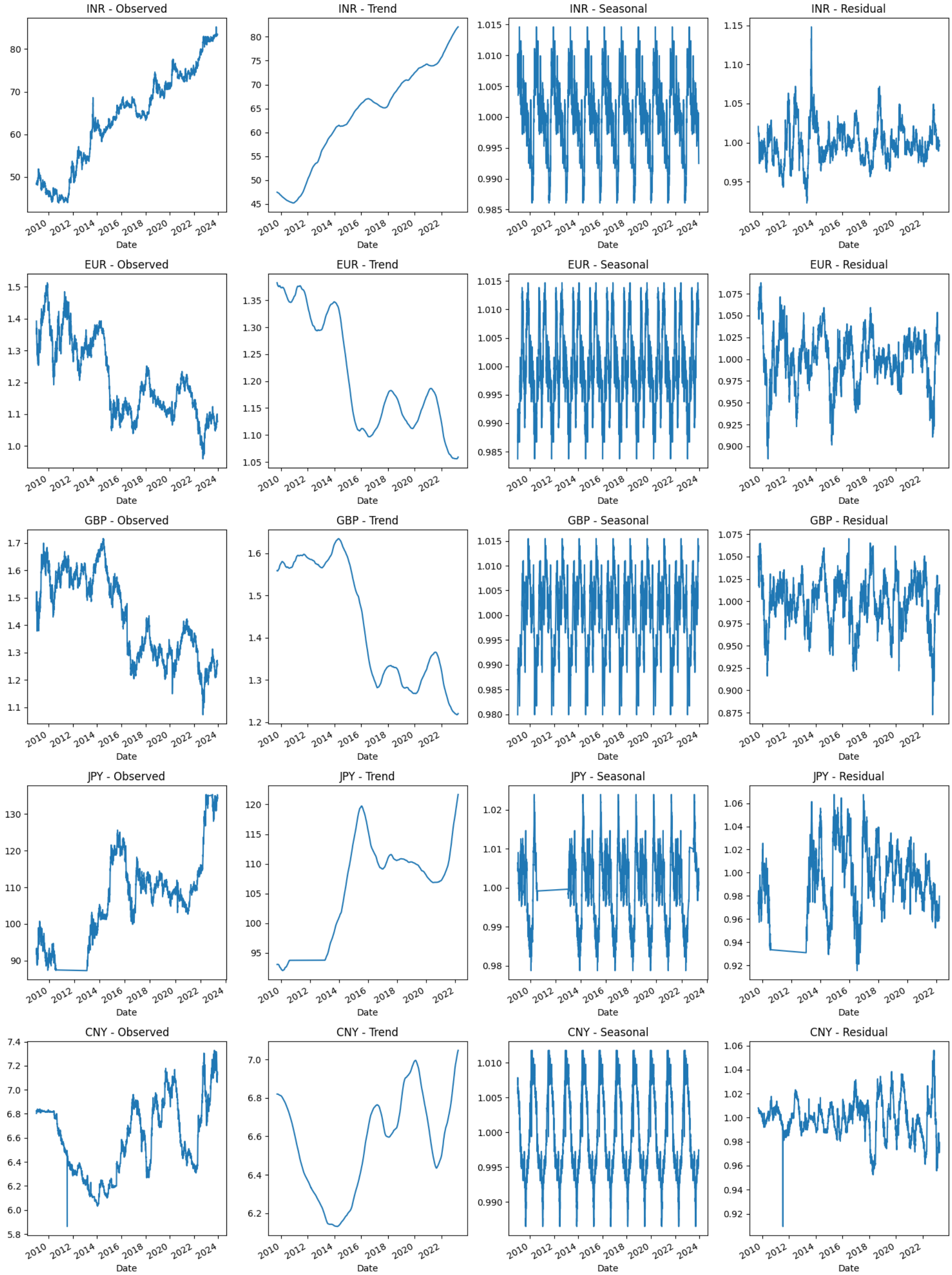

Fig.3 Decomposition Analysis of currency rates for all currencies

The data is free from all the outliers that would negatively influence the model performance. To analyze the data, we tried to decompose the data and observe if there was any trend, seasonality or noise present in the data. Our initial analysis of volatility (as seen in the Fig.2) showed that the data before 2008 was not entirely helpful in training the data because of the economic crash that weakened the currencies worldwide, mainly the USD, and hence, a very high volatility was recorded for the currencies in consideration. Hence, to avoid the possibility of this being considered as a trend by the model, we only considered the data after the 2008 economic crisis.

From the decomposition analysis in **Fig.3** , we notice that currencies like INR, EUR, and GBP have a clear trend, i.e, INR has been increasing since 2010 while EUR and GBP have consistently weakened over the years. This observation suggests that the models with these currencies will fit better than currencies like JPY and CNY, where a clear trend is not particularly visible. We also observed that the closing currency values do not follow a normal distribution.

Looking at the decomposition graphs, we observed that the GBP and EUR currency rates have similar patterns throughout the historical data. To check for linear interdependence, we performed a simple correlation analysis of the different currencies in consideration. We found that GBP and EUR are more strongly correlated than other pairs, which is evident in the trend patterns of both currencies. This observation makes sense given the geographical proximities and interdependencies of the European economies. Hence, we tried to incorporate the EUR closing price while making estimations for GBP closing price.

Now, that we have identified general trends in the data, we can say that the model would not have an accurate prediction from just the closing prices, and hence, we need to add more features that would indicate the patterns and help in learning.

PART 3: Feature Engineering

We know that the Prophet model is designed to handle many varities of time series data automatically, without having to preprocess the data specifically. This advantage did not necessitate on normalizing the features. However, adding more relevant features that would help the model capture the patterns better would be beneficial in improving the model performance. Keeping this mind, we designed certain features that would help us capture the trends and which the model can use.

1. **Open Price**: This is also the previous day's close price. Since, the currency prices don't fluctuate on large values, adding the open price as a regressor for the model will help in the predictions.
2. **Lag Features (Close_lag_N)**
   a. Purpose: Captures autocorrelation by including previous values (lags) of the target variable.
   b. Application in Currency Rates: Helps in understanding how past closing prices might influence future trends.
   c. Formula:**Close_lag_N=Close$_{(t-N)}$,**
   Where N is the lag period, and t is the current time step
3. **Moving Averages (Close_MA_N)**
   a. Purpose: Smoothens short-term fluctuations to reveal longer-term trends.
   b. Application in Currency Rates: Assists in identifying the overall trend direction over a chosen period.
   c. Formula:

$$\text{Close\_MA\_N} = \frac{1}{N} \sum_{i=t-N+1}^{t} \text{Close}_i$$

   Where N is the window size for the moving average, and i ranges over the window
4. **Relative Strength Index (RSI)**
   a. Purpose: A momentum oscillator that measures the speed and change of price movements.
   Application in Currency Rates: Indicates potential price reversals.
   Formula:

$$\mathrm{RSI} = 100 - \frac{100}{1 + \mathrm{RS}}$$

Where RS (Relative Strength) is the average of N days' up closes divided by the average of N days' down closes.

After the feature engineering, the input data for the machine learning model looks like the following snippet:

index	Date	Open	High	Low	Close	Adj Close	Currency_Pair	Return	Volatility	Close_lag_7	Close_MA_5	RSI
23528	2009-01-01 0:00	48.065	48.825	48.065	48.065	48.06499863	INR	0	0.1104825002	48.63	48.0218	47.65883878
23529	2009-01-02 0:00	48.065	49.075	48.065	48.245	48.24499893	INR	0.003744935199	0.1105003543	48.072	48.1636	48.76179245
23530	2009-01-05 0:00	48.8	48.8	48.196	48.229	48.22900009	INR	-0.00033161655	0.1105031279	48.683	48.2843	56.09520746
23531	2009-01-06 0:00	48.5	48.76	48.45	48.505	48.50500107	INR	0.005722718199	0.1103709029	48.683	48.3139	53.87199731
23532	2009-01-07 0:00	48.503	48.838	48.37	48.551	48.55099869	INR	0.000948306744	0.110370077	48.017	48.3014	57.74204244
23533	2009-01-08 0:00	48.563	48.668	48.33	48.365	48.36500168	INR	-0.00383096155	0.1104625597	48.45	48.3493	68.47109042
23534	2009-01-09 0:00	48.453	49.12	48.023	48.468	48.4679985	INR	0.002129573506	0.1104263236	48.065	48.3175	63.40674884
23535	2009-01-12 0:00	48.3	48.858	48.3	48.492	48.49200058	INR	0.000495214903	0.1102761113	48.065	48.296	56.43492904
23536	2009-01-13 0:00	48.808	49.128	48.76	48.87	48.86999893	INR	0.007795066146	0.1104929243	48.245	48.3435	48.0195178
23537	2009-01-14 0:00	48.918	48.938	48.388	48.65	48.65000153	INR	-0.00450168632	0.1106211562	48.229	48.3855	62.07627119
23538	2009-01-15 0:00	48.793	49.133	48.643	48.67	48.66999817	INR	0.000411030677	0.1106186483	48.505	48.444	49.43357364
23539	2009-01-16 0:00	48.898	48.898	48.498	48.643	48.64300156	INR	-0.00055468694	0.1106008165	48.551	48.5045	49.77838391
23540	2009-01-19 0:00	48.78	48.78	48.506	48.539	48.53900146	INR	-0.00213802784	0.1106324737	48.365	48.5443	63.64428945
23541	2009-01-20 0:00	48.518	49.203	48.518	48.909	48.9090004	INR	0.007622714121	0.1105871996	48.468	48.5753	52.26463104
23542	2009-01-21 0:00	49.043	49.27	48.918	49.133	49.13299942	INR	0.004579914159	0.110628062	48.492	48.6157	71.64102564
23543	2009-01-22 0:00	49.043	49.173	48.858	49.081	49.08100128	INR	-0.00105831394	0.1106374968	48.87	48.6739	74.56301748
23544	2009-01-23 0:00	49.098	49.283	48.61	49.018	49.01800156	INR	-0.00128358679	0.110658354	48.65	48.7455	70.43010753
23545	2009-01-26 0:00	48.628	48.628	48.43	48.469	48.46900177	INR	-0.01119996265	0.1113162448	48.67	48.8005	68.84854276
23546	2009-01-27 0:00	48.518	48.933	48.518	48.791	48.79100037	INR	0.006643392363	0.111394685	48.643	48.7982	49.23922232
23547	2009-01-28 0:00	48.878	48.918	48.755	48.792	48.79199982	INR	2.05E-05	0.1113758895	48.539	48.7903	54.54201363
23548	2009-01-29 0:00	48.823	49.013	48.503	48.873	48.8730011	INR	0.00166013449	0.1113679171	48.909	48.8045	58.68945869
23549	2009-01-30 0:00	48.503	49.1	48.503	48.733	48.73300171	INR	-0.00286455479	0.1114224116	49.133	48.8248	58.31622177
23550	2009-02-02 0:00	48.733	49.08	48.613	48.925	48.92499924	INR	0.003939784568	0.1114634006	49.081	48.8338	54.72363779

PART 4: Model Creation

Prophet model is one of the most versatile machine leaning models to be used for time series predictions. However, tuning the parameters of the model is crucial for better performance. In our decomposition analysis, we noticed that there was seasonality observed in the data. Hence, we set the following parameters to true:

Weekly_seasonality = True : to capture the weekly seasonal trends

daily_seasonality = True : to capture any daily seasonal trends

yearly_seasonality = True : to capture any yearly season trends

seasonality_mode = ‘multiplicative’ as observed in the decomposition analysis.

Apart from the tuning the hyperparameters, we also the custom features as model regressors (lag feature, moving average, and RSI) to the model.

After setting up one model for each currency pair, we created split on test and train datasets to evaluate the model. After sorting the data by date in ascending order, given the huge number of datapoints, we split the data into 90% as training data and 10% as testing data to evaluate the model performance.

OBSERVATIONS:

The basis of our model evaluation was both qualitative and quantitive. To quantitively evaluate the model performance for each currency, we employed the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The metrics were calculated as shown below:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}|$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y})^2$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y})^2}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2}$$

Where,

$\hat{y}$ − *predicted value of y*

$\bar{y}$ − *mean value of y*

	MAPE	RMSE	MAE
EUR	0.08%	0.00144	0.008
JPY	0.87%	0.13115654	0.111464
INR	0.05%	0.04404825	0.039415
CNY	0.12%	0.010197	0.0085065
GBP	0.12%	0.001499	0.0014

The performance was satisfactory given the values of each metric. We tried to see the goodness of fit in each case and tried to visualize the trends in that the model observed while training for the data. We also ensured that the model was overfitting in the training data. The graphs of the these are as follows:

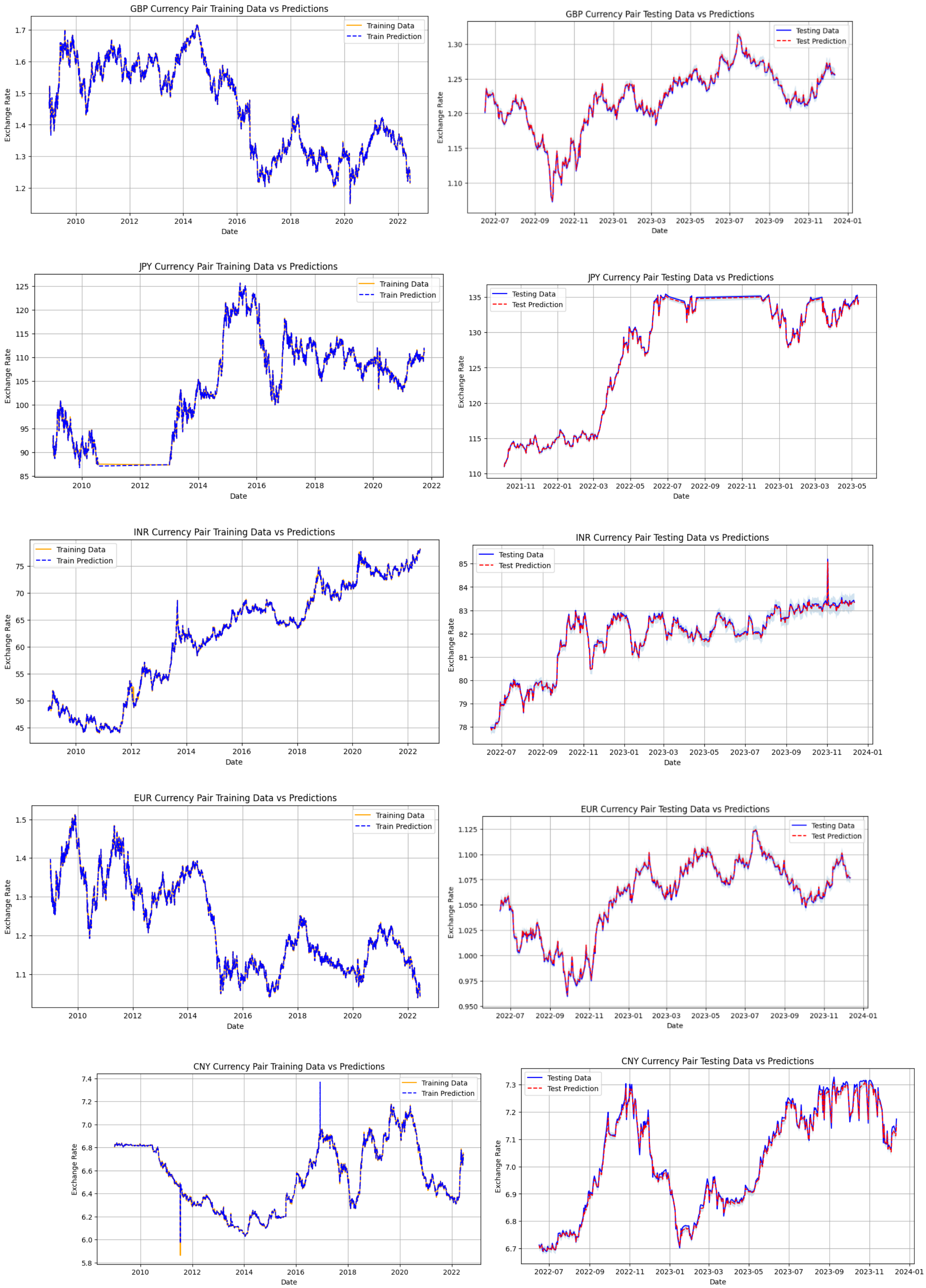

Fig.4: Visualizations of model performance on train and test to asses the goodness of fit for each currency pair

PART 5: Forecasting

After seeing the satisfactory model performance on each currency pair, entire historical dataset was used to train the model. The additional features which were created to assist the model prediction (regressors) were calculated as when the modle made a prediction. Overall, the model was used to forecast 7 values of closing prices into the future for each currency pair. The future dates were calculated by taking the last available date for in the final training dataset for each currency. The forecast values from the model for each currency pair are as follows:

Date	Close	High	Low	Currecy Pair
2023-12-13 0:00	83.37285537	83.56851489	83.18120001	INR
2023-12-14 0:00	83.39174076	83.58332849	83.2113303	INR
2023-12-15 0:00	83.41413734	83.60406521	83.21226056	INR
2023-12-18 0:00	83.42250599	83.60944246	83.2294999	INR
2023-12-19 0:00	83.45691207	83.64663295	83.27410641	INR
2023-12-20 0:00	83.47411913	83.65877341	83.27423475	INR
2023-12-21 0:00	83.48993432	83.67027628	83.30622674	INR

Date	Close	High	Low	Currency Pair
2023-12-13 0:00	1.076108987	1.080007046	1.07231019	EUR
2023-12-14 0:00	1.075577477	1.079638358	1.071448546	EUR
2023-12-15 0:00	1.07496261	1.07919521	1.071273167	EUR
2023-12-18 0:00	1.074271776	1.078498044	1.070257799	EUR
2023-12-19 0:00	1.073553555	1.077423799	1.069443209	EUR
2023-12-20 0:00	1.07298106	1.077121231	1.069208154	EUR
2023-12-21 0:00	1.072470732	1.076515435	1.068575979	EUR

Date	Close	High	Low	Currency Pair
2023-12-12 0:00	1.2555	1.2608	1.2519	GBP
2023-12-13 0:00	1.255372451	1.259829918	1.250560316	GBP
2023-12-14 0:00	1.255258752	1.260097112	1.250056385	GBP
2023-12-15 0:00	1.2550011	1.259362149	1.250214105	GBP
2023-12-18 0:00	1.254857926	1.259435548	1.25025702	GBP
2023-12-19 0:00	1.254834646	1.259464179	1.250257551	GBP
2023-12-20 0:00	1.254808935	1.259829736	1.250042705	GBP
2023-12-21 0:00	1.254823713	1.259550765	1.250035315	GBP

Date	Close	High	Low	Currency Pair
2023-12-13 0:00	7.168604595	7.180888992	7.157283849	CNY
2023-12-14 0:00	7.160486318	7.17327182	7.14835685	CNY
2023-12-15 0:00	7.155870708	7.167923456	7.144319081	CNY
2023-12-18 0:00	7.153531984	7.167050042	7.141396067	CNY
2023-12-19 0:00	7.152491454	7.165076355	7.140475446	CNY
2023-12-20 0:00	7.155727884	7.167483442	7.143861817	CNY
2023-12-21 0:00	7.155769513	7.168112765	7.143307305	CNY

Date	Close	High	Low	Currency_Pair
2023-12-13 0:00:00	146.1218736	146.4086699	145.8291149	JPY

2023-12-14 0:00:00	146.1746777	146.45913	145.8772388	JPY
2023-12-15 0:00:00	146.2323407	146.5221065	145.955092	JPY
2023-12-18 0:00:00	146.2944695	146.5987415	146.0162565	JPY
2023-12-19 0:00:00	146.3006559	146.5739078	146.0124244	JPY
2023-12-20 0:00:00	146.3288447	146.587286	146.039833	JPY
2023-12-21 0:00:00	146.3757837	146.6526365	146.088892	JPY

PART 6: Front-End

Overview

This web application, developed using Streamlit, is designed to provide users with predictions on currency exchange rates. The application is intuitive and user-friendly, offering a seamless experience for individuals interested in financial analysis, forex trading, or general currency exchange inquiries. It combines sophisticated forecasting models with an interactive front-end interface.

Key Features

User Interface:

•A clean and straightforward layout with a primary focus on functionality.

•Interactive sidebar for currency pair selection, enhancing user engagement.

•A central display for predictions, offering clarity and immediate access to forecasted data.

Currency Pair Selection:

•Users can choose from a predefined list of major currency pairs, including Euro to USD, USD to Japanese Yen, British Pound to USD, etc.

•The selection mechanism is implemented via a radio button in the sidebar, allowing for easy and quick navigation.

Prediction Generation:

•Upon selecting a currency pair and clicking the 'Generate Prediction' button, the application displays a predictive chart.

•The system leverages pre-built forecasting models for each currency pair, ensuring accurate and reliable predictions.

Data Visualization:

•Utilizes Altair for creating dynamic and interactive line charts.

•Charts display predicted exchange rates over time, clearly differentiating between past and future values.

•Customizable chart properties such as width and height, tailored for optimal user experience.

Data Presentation:

•Forecasts are categorized as 'future' or 'past' based on the current date, adding a temporal context to the predictions.

•A tabulated view of future predictions is provided, giving users a clear and concise summary of expected rates.

Technical Aspects

•Front-End Development: The application is built using Streamlit, a powerful tool for creating data applications with Python. Streamlit's simplicity and efficiency allow for rapid development and deployment.

•Data Handling and Processing: The application assumes the presence of external functions and data sources for generating predictions. These are integral to the application's functionality and are expected to be part of a larger data processing module.

•Visualization: Altair is employed for creating sophisticated visual representations of the predicted data, chosen for its interactivity and aesthetic appeal.
Usage Scenarios
•Financial Analysis: Useful for analysts tracking and predicting currency market trends.
•Forex Trading: Traders can leverage the predictions for making informed trading decisions.
•General Public: Individuals planning foreign investments or currency exchange can benefit from the forecasts.

Conclusion
This web application stands out for its ease of use, accurate predictions, and clear presentation of data. It serves as a valuable tool for anyone interested in currency exchange rates, offering insights into future trends and aiding in decision-making processes. With its streamlined interface and robust backend, it caters to both professional and casual users, making it a versatile tool in the financial technology space.

Steps to access the webpage:

To access the Currency Exchange Rate Prediction web application, you can use the Streamlit command to run the application directly from its Python file. Here's how:
1.Open Your Command Line or Terminal:
•On Windows, you can use Command Prompt or PowerShell.
•On macOS or Linux, you can use the Terminal.

2.Navigate to the Directory:
•If your Python file (e.g., app.py) is not in the current directory, navigate to the directory where the file is located using the cd command.

3.Run the Streamlit Command:
•Execute the command: streamlit run [python file location]
•Replace [python file location] with the path to your Python file. For example, if your file is named app.py and located in the current directory, the command would be streamlit run app.py.
•If your file is in a different directory, provide the full path. For example: streamlit run C:\Users\YourName\Documents\app.py.

4.Access the Web Application:
•Once you run the command, Streamlit will start the server and host your web application.
•Your default web browser should automatically open and navigate to the application. If it doesn't, Streamlit will provide a local URL (like http://localhost:8501) in the command line or terminal, which you can manually enter in your web browser to access the application.

Select Currency

- Euro to USD
- USD to Japanese Yen
- British Pound to USD
- USD to Indian Rupee
- USD to Chinese Yuan

Deploy

Currency Exchange Rate Prediction

Generate Prediction

Exchange Rate Prediction Chart for Euro to USD

Date	Predicted Exchange Rate
2023-12-13 00:00:00	1.0751
2023-12-14 00:00:00	1.0745
2023-12-15 00:00:00	1.0738
2023-12-18 00:00:00	1.073
2023-12-19 00:00:00	1.0722
2023-12-20 00:00:00	1.0716

Exchange Rate Prediction Chart for USD to Japanese Yen