I'll start this task of Currency Exchange Rate Forecasting by importing the necessary Python libraries and the dataset:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
data = pd.read_csv("INR-USD.csv")
print(data.head())
                                                      Close Adj Close Volume
                                  High
             Date
                       0pen
                                             Low
    0 2003-12-01 45.709000 45.728001 45.449001 45.480000 45.480000
       2003-12-08 45.474998 45.507999 45.352001
                                                  45.451000 45.451000
                                                                          0.0
    2 2003-12-15 45.450001 45.500000 45.332001 45.455002 45.455002
                                                                          0.0
       2003-12-22 45.417000 45.549000 45.296001 45.507999 45.507999
                                                                          0.0
    4 2003-12-29 45.439999 45.645000 45.421001 45.560001 45.560001
                                                                          0.0
```

check if the dataset contains any missing values before moving forward:

```
print(data.isnull().sum())

Date     0
Open     3
High     3
Low     3
Close     3
Adj Close     3
Volume     3
dtype: int64
```

The dataset has some missing values. Here's how to remove them:

```
data = data.dropna()
```

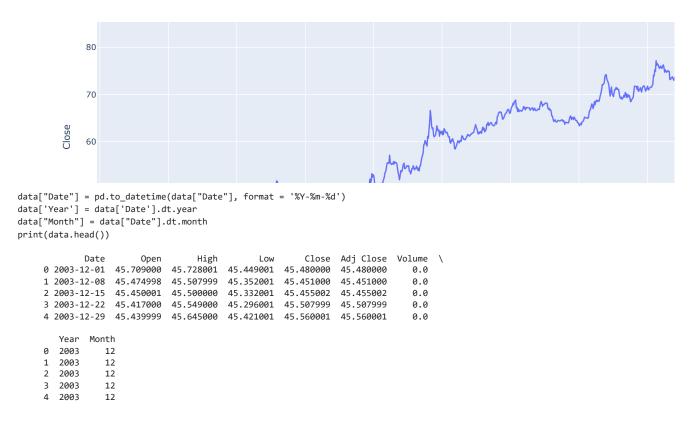
Now let's have a look at the descriptive statistics of this dataset:

print(data.describe())

	Open	High	Low	Close	Adj Close	Volume
count	1013.000000	1013.000000	1013.000000	1013.000000	1013.000000	1013.0
mean	58.035208	58.506681	57.654706	58.056509	58.056509	0.0
std	12.614635	12.716632	12.565279	12.657407	12.657407	0.0
min	38.995998	39.334999	38.979000	39.044998	39.044998	0.0
25%	45.508999	45.775002	45.231998	45.498001	45.498001	0.0
50%	59.702999	60.342999	59.209999	59.840000	59.840000	0.0
75%	68.508499	69.099998	68.250000	68.538002	68.538002	0.0
max	82.917999	83.386002	82.563004	82.932999	82.932999	0.0

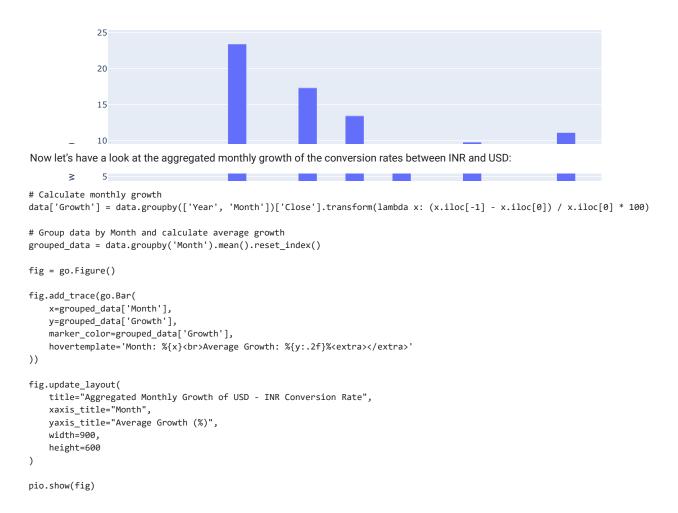
As we are using the USD – INR conversion rates data, let's analyze the conversion rates between both currencies over the years. I'll start with a line chart showing the trend of conversion rates over the years:

USD - INR Conversion Rate over the years

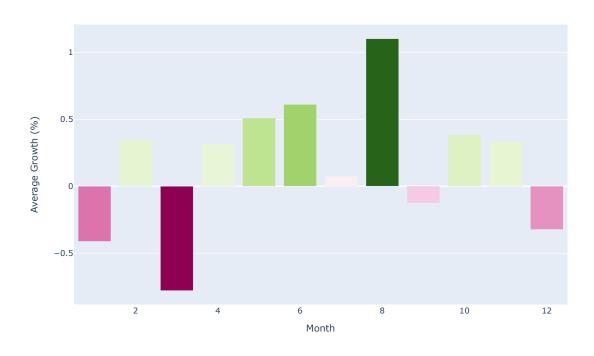


Now let's have a look at the aggregated yearly growth of the conversion rates between INR and USD:

Yearly Growth of USD - INR Conversion Rate



Aggregated Monthly Growth of USD - INR Conversion Rate



Forecasting Exchange Rates Using Time Series Forecasting

We will use time series forecasting to forecast exchange rates. To choose the most appropriate time series forecasting model, we need to perform seasonal decomposition, which will help us identify any recurring patterns, long-term trends, and random fluctuations present in the USD – INR exchange rate data:

```
from statsmodels.tsa.seasonal import seasonal_decompose
result = seasonal_decompose(data["Close"], model='multiplicative', period=24)
fig = plt.figure()
fig = result.plot()
fig.set_size_inches(8, 6)
fig.show()
     <Figure size 640x480 with 0 Axes>
                                                         Close
            80
            60
            40
                               200
                                                 400
                                                                  600
                                                                                    800
                                                                                                     1000
            80
         Trend
            60
            40
                                                 400
                                                                  600
                                                                                    800
                                                                                                     1000
                               200
         0.995
                                                                                    800
           1.0
           0.5
           0.0
                               200
                                                 400
                                                                  600
                                                                                    800
                                                                                                     1000
from pmdarima.arima import auto_arima
model = auto_arima(data['Close'], seasonal=True, m=52, suppress_warnings=True)
print(model.order)
     (2, 1, 0)
p, d, q = 2, 1, 0
from statsmodels.tsa.statespace.sarimax import SARIMAX
model = SARIMAX(data["Close"], order=(p, d, q),
                seasonal\_order=(p, d, q, 52))
fitted = model.fit()
print(fitted.summary())
    /usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarning:
```

An unsupported index was provided and will be ignored when e.g. forecasting.

 $/usr/local/lib/python 3.10/dist-packages/stats models/tsa/base/tsa_model.py: 471:\ Value Warning: a constant of the packages of the packages$

An unsupported index was provided and will be ignored when e.g. forecasting.

pio.show(fig)

```
SARIMAX(2, 1, 0)x(2, 1, 0, 52)
                                                                                                         Log Likelihood
                                                                                                                                                                 -905 797
         Model:
         Date:
                                                                      Tue, 30 May 2023
                                                                                                                                                                 1821,594
                                                                                                                                                                1845.929
         Time:
                                                                                   16:35:32
                                                                                                         BIC
         Sample:
                                                                                                 a
                                                                                                         HOIC
                                                                                                                                                                 1830.861
                                                                                         - 1013
         Covariance Type:
                                                                                             opg
         ______
                                    coef std err
                                                                                             P>|z| [0.025 0.975]
         -----
                         0.0313
                                                        0.026 1.193
0.026 2.481
                                                                                                                 -0.020
0.013
         ar.L1
                                                                                                  0.233
                                                                                                                                              0.083
         ar.L2
                                   0.0643
                                                                                                   0.013
                                                                                                                                              0.115
                               0.0043 0.026 2.481 0.013

-0.6358 0.026 -24.677 0.000

-0.3075 0.029 -10.602 0.000

0.3767 0.013 28.481 0.000
         ar.S.L52
                                                                                                                       -0.686
                                                                                                                                             -0.585
                             -0.3075
                                                                                                                       -0.364
         ar.S.L104
                                                                                                                -0.364
0.351
                                                                                                                                              0.403
         sigma2
          Ljung-Box (L1) (Q):
                                                                             0.00 Jarque-Bera (JB):
         Prob(Q):
                                                                             0.99 Prob(JB):
                                                                                                                                                           0.00
         Heteroskedasticity (H):
                                                                             1.57
                                                                                                                                                           9.96
                                                                                           Skew:
         Prob(H) (two-sided):
                                                                              0.00 Kurtosis:
                                                                                                                                                           4.47
         ______
         [1] Covariance matrix calculated using the outer product of gradients (complex-step).
predictions = fitted.predict(len(data), len(data)+60)
print(predictions)
         1013
                       81.732807
         1014
                       81.886990
         1015
                       82,180319
         1016
                       82.607754
         1017
                       82.474242
                      84.906873
         1069
         1070
                       85.402528
         1071
                       85.520223
         1072
                       85.830554
         1073
                       85.687360
         Name: predicted_mean, Length: 61, dtype: float64
         /usr/local/lib/python 3.10/dist-packages/stats models/tsa/base/tsa\_model.py: 834: \ Value Warning: lib/python 3.10/dist-packages/stats models/tsa/base/tsa\_models/tsa/base/stats models/tsa/base/stats models/tsa/base/sta
         No supported index is available. Prediction results will be given with an integer index beginning at `start`.
Here's how to visualize the forecasted results:
# Create figure
fig = go.Figure()
# Add training data line plot
fig.add_trace(go.Scatter(
      x=data.index,
      y=data['Close'],
      mode='lines',
      name='Training Data',
      line=dict(color='blue')
))
# Add predictions line plot
fig.add_trace(go.Scatter(
      x=predictions.index,
      y=predictions,
      mode='lines',
      name='Predictions'.
       line=dict(color='green')
))
fig.update_layout(
      title="INR Rate - Training Data and Predictions",
      xaxis title="Date",
      yaxis_title="Close",
      legend_title="Data",
       width=900,
       height=600
)
```

INR Rate - Training Data and Predictions

