END TRIMESTER EXAMINATION

A Project Report submitted in partial fulfillment of the requirements for the degree of Master of Business Administration

By

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INTRODUCTION:

In the world of finance, understanding how different market indices and economic factors interact is crucial for making smart investment decisions. The **S&P 500 Index (SPX)** is one of the most important measures of the U.S. stock market. It tracks the performance of 500 large companies in the U.S. When the S&P 500 goes up, it generally signals that investors are confident about the economy. If it goes down, it may indicate concerns about economic growth or company profits.

On the other hand, the **INViXN Index** measures the level of uncertainty or fear in India's stock market. It's often called India's "fear index" because it shows how worried investors are about market risks. When the INViXN is high, it means that investors are more anxious about the future, which could be due to political, economic, or global events that may impact the Indian market.

Additionally, the **exchange rate between the U.S. Dollar (USD) and the Indian Rupee (INR)** is an important factor that influences both local businesses and global markets. A stronger U.S. dollar can make it more expensive for India to export goods to other countries and can increase the cost of importing products. On the flip side, a weaker rupee can lead to higher prices for imported goods, contributing to inflation. This exchange rate also plays a big role in foreign investment decisions, as investors look for stability and favorable currency values when deciding where to put their money.

Overall, understanding how these three elements—the **S&P 500**, the **INViXN**, and the **USD-INR exchange rate**—work together helps investors make better decisions by looking at both the local and global financial picture.

OBJECTIVE:

This analysis aims to predict the difference between two major stock market indices: the S&P 500 Index (SPX) from the U.S. and the INViXN Index, which tracks volatility in the Indian stock market. To improve the accuracy of our predictions, we will also look at how the USD to INR exchange rate (the value of the U.S. dollar compared to the Indian rupee) affects the relationship between these indices. Since currency exchange rates can influence market trends and investor confidence, understanding this interaction can give us better insights into market behavior and investment opportunities.

PROBLEM STATEMENT:

Global markets are connected, meaning changes in one country's economy often impact others. Investors need to understand the relationship between stock markets in different countries to make smarter investment choices. However, predicting how the U.S. and Indian markets relate to each other is challenging, especially with the added factor of exchange rate fluctuations between the U.S. dollar and Indian rupee.

This analysis focuses on:

- Forecasting the difference between the U.S. stock market (SPX) and Indian market volatility (INViXN).
- Incorporating the effect of USD/INR exchange rate changes on this relationship.
- Providing insights that help investors predict future trends and make informed decisions.

DATA OVERVIEW:

The data for this analysis is sourced from Bloomberg and covers a time period from 2014 to August 2024. The key variables include the SPX Index (representing the U.S. stock market), the INViXN Index (which measures market volatility in India), and the USD to INR exchange rate (reflecting the value of the U.S. dollar against the Indian rupee). The data has been aggregated on a monthly basis, allowing us to observe long-term trends and interactions between these variables over the 10-year period.

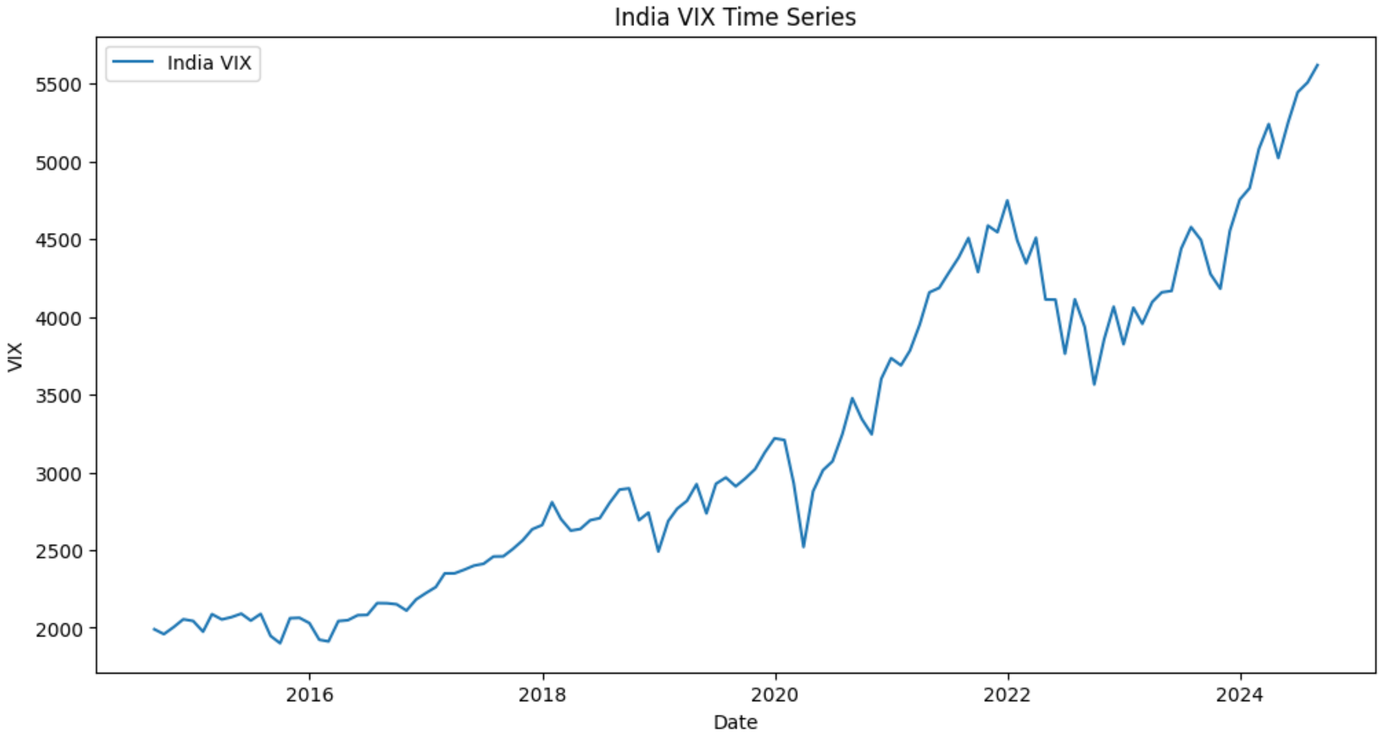
```
       Date  SPX Index  (L1)  INVIXN Index  (R1)  SPX Index - INVIXN Index  \
0  31/08/14          2003.37              13.0675                 1990.3025
1  30/09/14          1972.29              13.1450                 1959.1450
2  31/10/14          2018.05              13.2950                 2004.7550
3  30/11/14          2067.56              12.8975                 2054.6626
4  31/12/14          2058.90              15.1200                 2043.7800

   Exchange Rate (USD to INR)
0                   78.074402
1                   75.393422
2                   78.925590
3                   71.865701
4                   78.036721
```

DATA PREPROCESSING:

To ensure the dataset was ready for analysis, several preprocessing steps were carried out. First, the 'Date' column was converted to a proper Date type, allowing for accurate time-based operations such as sorting and grouping. Afterward, the dataset was carefully examined for any missing values, which were either filled or removed to prevent inaccuracies in the analysis. Additionally, irrelevant columns that did not contribute to the objective of the study were removed, streamlining the dataset for efficiency. The data was then aggregated by month and year, transforming daily records into monthly summaries. This aggregation helped to capture broader trends over time, making the analysis more manageable and insightful for long-term forecasting.

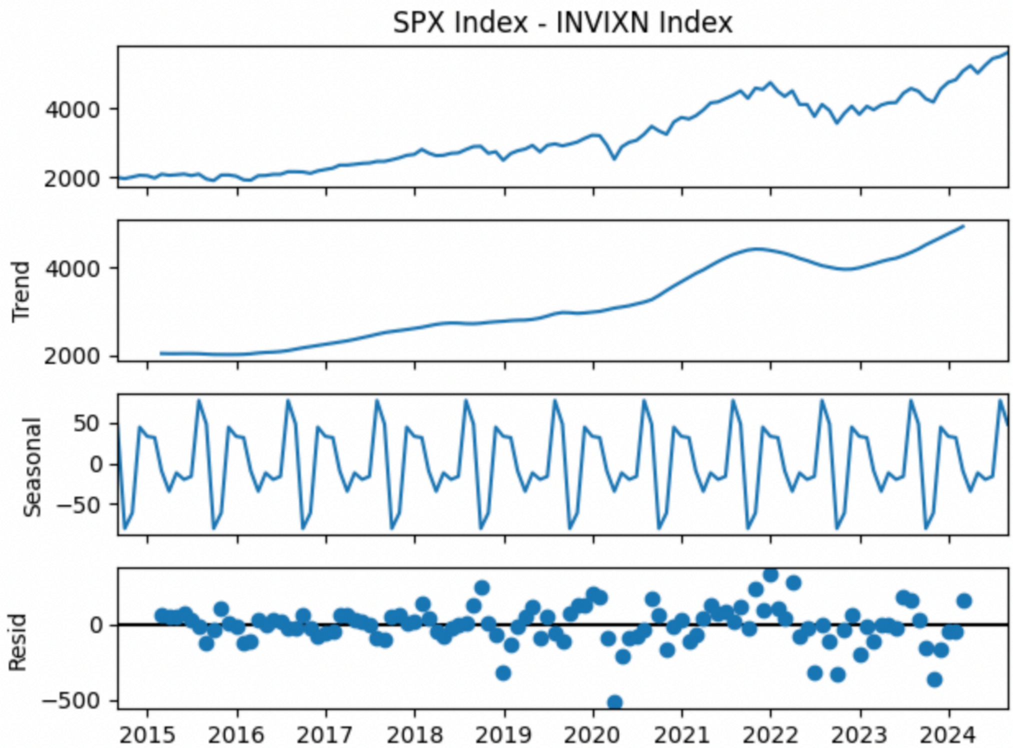
Date	SPX Index - INVIXN Index	Exchange Rate (USD to INR)
2014-08-31	1990.3025	78.074402
2014-09-30	1959.1450	75.393422
2014-10-31	2004.7550	78.925590
2014-11-30	2054.6626	71.865701
2014-12-31	2043.7800	78.036721
...	...	...
2024-04-30	5022.8198	71.560186
2024-05-31	5252.9077	75.986585
2024-06-30	5446.6777	77.319939
2024-07-31	5509.0498	79.507143
2024-08-31	5621.0576	73.745401

TIME SERIES VISUALIZATIONS:



The time series plot of the India VIX from 2016 to 2024 illustrates a general upward trend in market volatility. This trend indicates that, overall, market uncertainty has increased during this period. However, the plot also shows notable fluctuations, suggesting that there have been significant periods of both low and high volatility. In recent years, particularly elevated levels of volatility are evident, which could be attributed to a variety of factors including economic uncertainty, geopolitical events, shifts in monetary policy, and global market dynamics.

TIME SERIES DECOMPOSITION:



The decomposition of the SPX Index - INVIXN Index time series reveals a pronounced upward trend, especially evident after 2019, indicating a steady increase in values over time. Alongside this trend, a strong seasonal pattern is observed, characterized by regular annual fluctuations that reflect recurring market behaviors or economic conditions. The residuals, representing the portion of variability not accounted for by the trend and seasonality, are centered around zero, suggesting that the model effectively captures most of the data's variance. This indicates that the series exhibits a clear trend and consistent seasonality with minimal unexplained noise, highlighting a well-modeled and reliable time series.

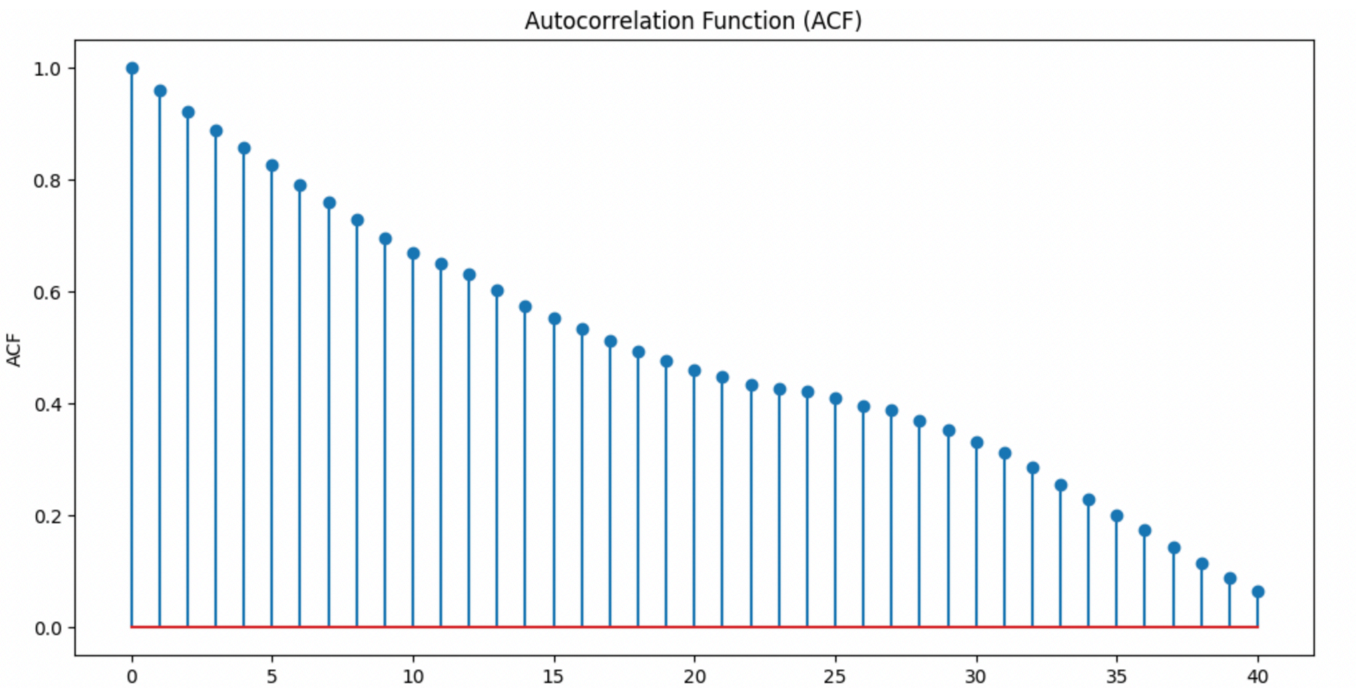
STATIONARITY CHECK:

```
[ ] # Check for stationarity using Augmented Dickey-Fuller test
    adf_result = adfuller(df_new['SPX Index - INVIXN Index'])
    print(f'ADF Statistic: {adf_result[0]}')
    print(f'p-value: {adf_result[1]}')
```

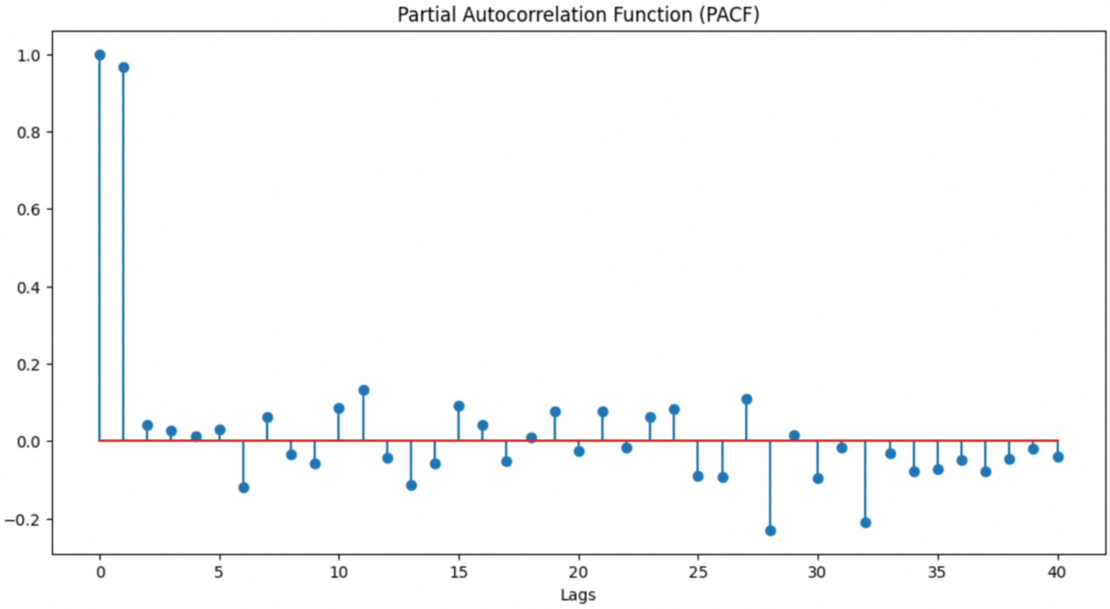
```
ADF Statistic: 0.6993721357691675
p-value: 0.9898253311670063
```

To address non-stationarity in the data, several transformation techniques were applied: differencing, logarithmic transformation, and Box-Cox transformation. Differencing, which involves subtracting the previous observation from the current one, was employed to remove trends and stabilize the mean. The logarithmic transformation aimed to stabilize the variance by compressing the scale of the data. Additionally, the Box-Cox transformation, which includes an optimal lambda parameter to normalize the data, was used to handle any remaining non-constant variance and improve normality. Despite these efforts, the data did not achieve stationarity. This suggests that the underlying non-stationarity may be due to more complex factors or patterns that are not adequately addressed by these common techniques, and further investigation or alternative methods might be required to achieve a stationary series.

ACF AND PACF



The Autocorrelation Function (ACF) plot shows a gradual decrease in the autocorrelation values as the lag increases, indicating a strong positive correlation between current and past values in the time series. The slow decay suggests that the series is not white noise and exhibits persistence or trend. This pattern is common in non-stationary time series, where past values significantly influence future values, making the series predictable based on its history.



The Partial Autocorrelation Function (PACF) plot shows significant correlation at lag 1, followed by a sharp drop to near-zero correlations at subsequent lags. This indicates that the series has a strong first-order autoregressive (AR) component, meaning that the current value of the series is primarily influenced by the immediately preceding value. The PACF suggests that the underlying time series might be well-modeled using an AR(1) process.

FORECASTING:

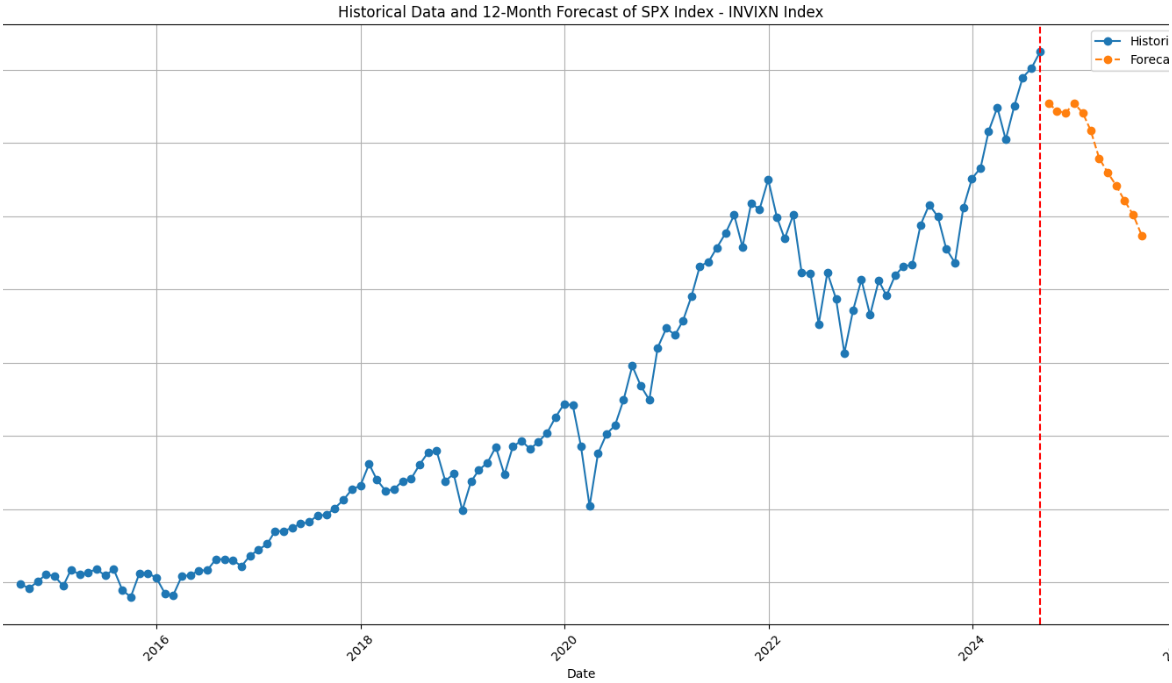
Models used :

1. RNN
2. CNN
3. LSTM
4. ARIMAX
5. ARCH
6. GARCH
7. ETS

- **RNN (Recurrent Neural Network)**: Ideal for capturing temporal dependencies and sequential patterns in financial time series data for accurate predictions.
- **CNN (Convolutional Neural Network)**: Useful for identifying spatial patterns and features in time series data, enhancing prediction accuracy through feature extraction.
- **LSTM (Long Short-Term Memory)**: Effective for modeling long-term dependencies and trends in time series, crucial for capturing complex patterns in financial data.
- **ARIMAX (AutoRegressive Integrated Moving Average with Exogenous Variables)**: Combines autoregressive and moving average models with external factors like the USD to INR exchange rate, improving prediction by incorporating additional influences.
- **ARCH (Autoregressive Conditional Heteroskedasticity)**: Suitable for modeling and forecasting volatility in financial time series, capturing changing variance over time.

- **GARCH (Generalized Autoregressive Conditional Heteroskedasticity)**: Extends ARCH by accounting for past volatility and errors, providing a more comprehensive model for predicting market volatility.
- **ETS (Exponential Smoothing)**: Focuses on capturing trend and seasonality in time series data, offering a straightforward approach for forecasting market movements.

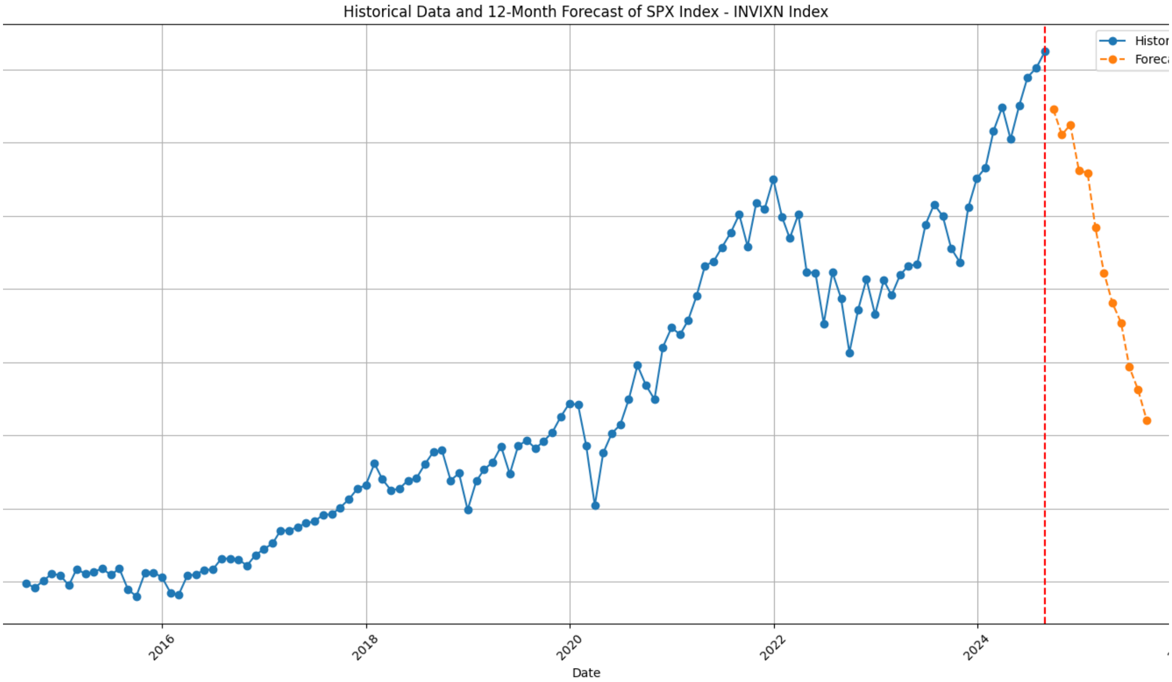
RNN:



Date	Predicted SPX-INVIXN
2024-09-30	5270.240234
2024-10-31	5219.143066
2024-11-30	5203.133789
2024-12-31	5271.219727
2025-01-31	5204.250977
2025-02-28	5087.201172
2025-03-31	4894.714844
2025-04-30	4798.795898
2025-05-31	4707.803223
2025-06-30	4604.140137
2025-07-31	4508.425293
2025-08-31	4365.572754

RNN stands for Recurrent Neural Networks. Here we have performed RNN and have got predicted values for the next 12 months.

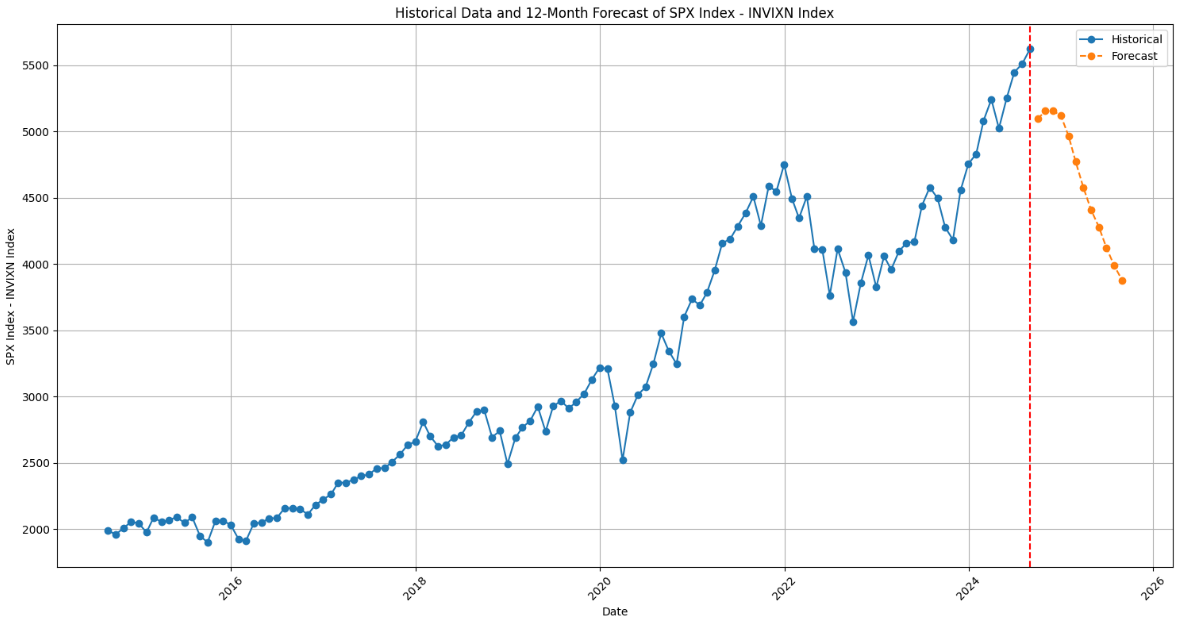
CNN:



	Date	Predicted SPX-INVIXN
0	2024-09-30	5226.377930
1	2024-10-31	5053.278809
2	2024-11-30	5121.243652
3	2024-12-31	4808.920410
4	2025-01-31	4793.231934
5	2025-02-28	4418.393555
6	2025-03-31	4109.840820
7	2025-04-30	3904.115723
8	2025-05-31	3769.438477
9	2025-06-30	3465.444336
10	2025-07-31	3311.136475

CNN stands for Convolutional Neural Networks. Here we have performed CNN and have got predicted values for the next 12 months

LSTM:

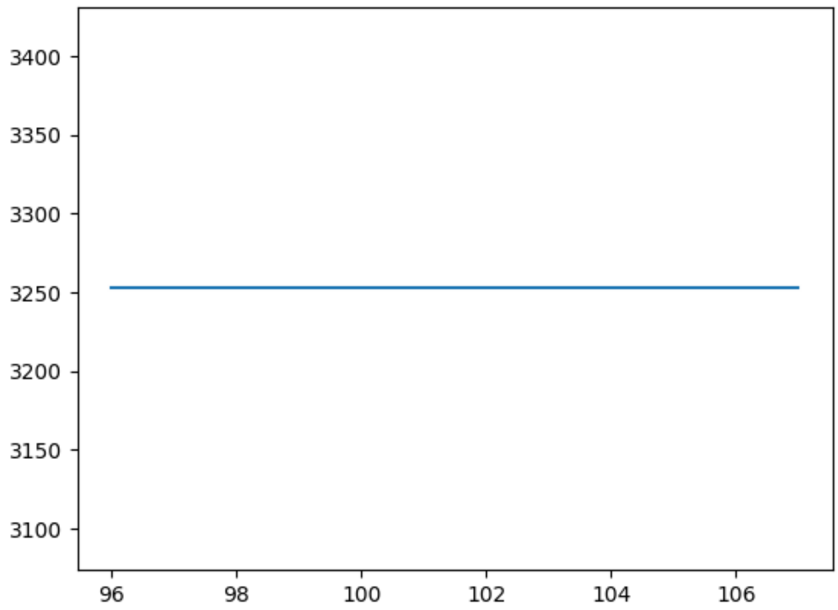


	Date	Predicted SPX-INVIXI
	2024-09-30	5093.93798
	2024-10-31	5153.54687
	2024-11-30	5154.35644
	2024-12-31	5120.54492
	2025-01-31	4965.49121
	2025-02-28	4771.75097
	2025-03-31	4573.83496
	2025-04-30	4408.77099
	2025-05-31	4278.75976
	2025-06-30	4122.21826
0	2025-07-31	3986.02441
1	2025-08-31	3877.93554

LSTM stands for Long Short – Term Memory. Here we have performed LSTM and have got predicted values for the next 12 months

ARIMAX:

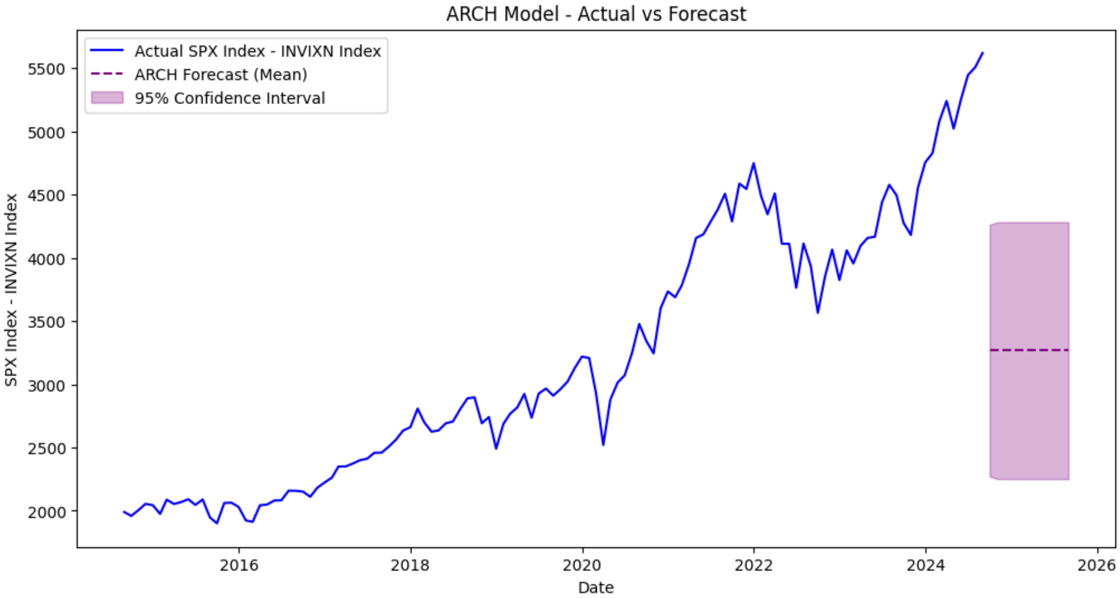
```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   96
Model:                        SARIMAX   Log Likelihood                -802.124
Date:                Mon, 02 Sep 2024   AIC                           1608.248
Time:                        05:14:30   BIC                           1613.377
Sample:                             0   HQIC                          1610.321
                                 - 96
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept   3252.4065    115.879     28.067      0.000    3025.288    3479.525
sigma2      1.059e+06   2.44e+05      4.338      0.000    5.81e+05    1.54e+06
===================================================================================
Ljung-Box (L1) (Q):                   1.08   Jarque-Bera (JB):                 7.10
Prob(Q):                              0.30   Prob(JB):                         0.03
Heteroskedasticity (H):               0.89   Skew:                             0.41
Prob(H) (two-sided):                  0.74   Kurtosis:                         1.95
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
96      3252.40653
97      3252.40653
98      3252.40653
99      3252.40653
100     3252.40653
101     3252.40653
102     3252.40653
103     3252.40653
104     3252.40653
105     3252.40653
106     3252.40653
107     3252.40653
```



Here we have performed ARIMAX and have got predicted values for the next 12 months.

ARCH MODEL:

```
                      Constant Mean - ARCH Model Results
==========================================================================================
Dep. Variable:     SPX Index - INVIXN Index   R-squared:                          0.000
Mean Model:                   Constant Mean   Adj. R-squared:                     0.000
Vol Model:                             ARCH   Log-Likelihood:                  -802.154
Distribution:                        Normal   AIC:                              1610.31
Method:                  Maximum Likelihood   BIC:                              1618.00
                                              No. Observations:                      96
Date:                      Thu, Sep 05 2024   Df Residuals:                          95
Time:                              08:50:56   Df Model:                               1
                                 Mean Model
==========================================================================
                 coef    std err          t      P>|t|    95.0% Conf. Int.
--------------------------------------------------------------------------
mu          3267.2055    112.929     28.932 4.784e-184 [3.046e+03,3.489e+03]
                              Volatility Model
==========================================================================
                 coef    std err          t      P>|t|    95.0% Conf. Int.
--------------------------------------------------------------------------
omega      9.5330e+05  1.541e+05      6.184  6.232e-10 [6.512e+05,1.255e+06]
alpha[1]       0.0773      0.128      0.602      0.547    [ -0.174,  0.329]
==========================================================================
```

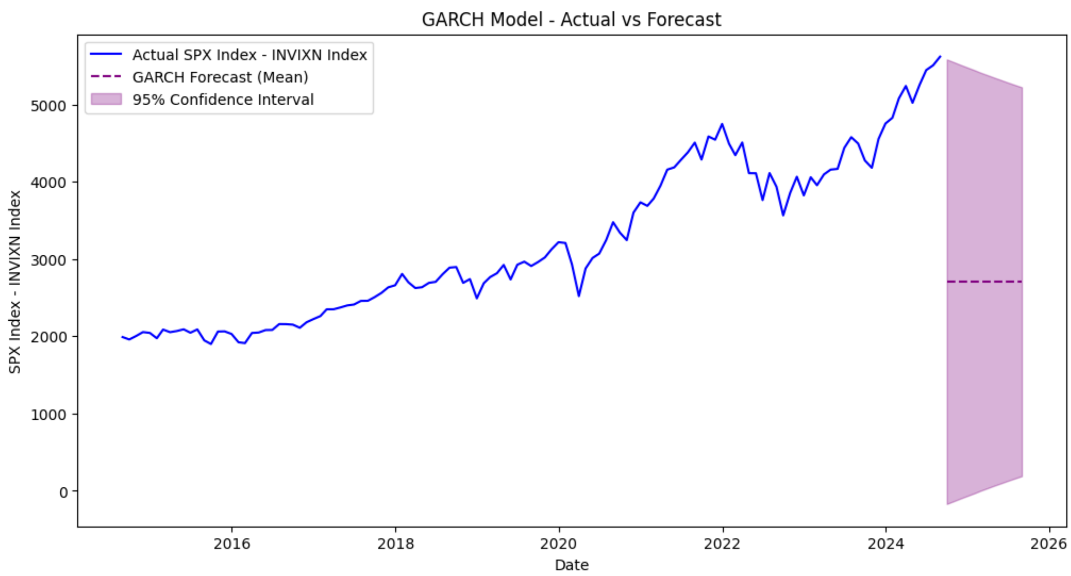



```
Forecasted Values from 09/24 to 08/25:
            Forecast Mean  Forecast Variance  Forecast Std Dev
2024-09-30    2709.754978       7.467137e+06       2732.606293
2024-10-31    2709.754978       6.590844e+06       2567.264006
2024-11-30    2709.754978       5.829462e+06       2414.427933
2024-12-31    2709.754978       5.167922e+06       2273.306394
2025-01-31    2709.754978       4.593131e+06       2143.159142
2025-02-28    2709.754978       4.093714e+06       2023.292864
2025-03-31    2709.754978       3.659787e+06       1913.056907
2025-04-30    2709.754978       3.282761e+06       1811.839234
2025-05-31    2709.754978       2.955176e+06       1719.062641
2025-06-30    2709.754978       2.670548e+06       1634.181251
2025-07-31    2709.754978       2.423244e+06       1556.677339
2025-08-31    2709.754978       2.208370e+06       1486.058515
```

ARCH model was performed to forecast the values for the next 12 months.

GARCH MODEL:

```
                     Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:     SPX Index - INVIXN Index   R-squared:                   0.000
Mean Model:                   Constant Mean   Adj. R-squared:              0.000
Vol Model:                            GARCH   Log-Likelihood:           -950.072
Distribution:                        Normal   AIC:                       1908.14
Method:                  Maximum Likelihood   BIC:                       1919.33
                                              No. Observations:              121
Date:                      Thu, Sep 05 2024   Df Residuals:                  120
Time:                              08:56:46   Df Model:                        1
                                 Mean Model
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
mu          2707.7415     56.852     47.628      0.000 [2.596e+03,2.819e+03]
                              Volatility Model
=============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
-----------------------------------------------------------------------------
omega      2.0579e+04  7.588e+04      0.271      0.786 [-1.281e+05,1.693e+05]
alpha[1]       0.9732      0.935      1.041      0.298      [ -0.859,  2.805]
beta[1]        0.0000      1.063      0.000      1.000      [ -2.083,  2.083]
=============================================================================
```



Forecasted Values from 09/24 to 08/25:

	Forecast Mean	Forecast Variance	Forecast Std Dev
2024-09-30	2707.741507	8.280186e+06	2877.531161
2024-10-31	2707.741507	8.078522e+06	2842.274175
2024-11-30	2707.741507	7.882272e+06	2807.538436
2024-12-31	2707.741507	7.691289e+06	2773.317339
2025-01-31	2707.741507	7.505432e+06	2739.604367
2025-02-28	2707.741507	7.324564e+06	2706.393091
2025-03-31	2707.741507	7.148550e+06	2673.677167
2025-04-30	2707.741507	6.977260e+06	2641.450336
2025-05-31	2707.741507	6.810568e+06	2609.706425
2025-06-30	2707.741507	6.648349e+06	2578.439340
2025-07-31	2707.741507	6.490485e+06	2547.643070
2025-08-31	2707.741507	6.336858e+06	2517.311683

GARCH model was performed to forecast the values for the next 12 months.

ETS MODEL:

```
Forecast for September 2024 to August 2025:
                Forecast
2024-09-30  5547.125221
2024-10-31  5631.892590
2024-11-30  5787.169278
2024-12-31  5826.339374
2025-01-31  5876.224090
2025-02-28  5910.395694
2025-03-31  5975.947698
2025-04-30  6027.435350
2025-05-31  6100.203360
2025-06-30  6174.651033
2025-07-31  6315.599183
2025-08-31  6337.886690
```

The ETS method was used for forecasting and the forecasted values for the next 12 months for

EVALUATION OF MODELS:

To evaluate the performance of the various time series models (RNN, CNN, LSTM, ARIMAX, ARCH, GARCH, and ETS), we have calculated the following metrics:

- AIC (Akaike Information Criterion): Measures the relative goodness of fit of a statistical model. Lower AIC values indicate better model fit.
- BIC (Bayesian Information Criterion): Similar to AIC, but penalizes more complex models. Lower BIC values also suggest better model fit.
- RMSE (Root Mean Squared Error): Measures the average magnitude of errors between predicted and actual values. Lower RMSE indicates better prediction accuracy.
- MSE (Mean Squared Error): The squared average of the errors. Lower MSE also indicates better prediction accuracy.

- MAE (Mean Absolute Error): The average absolute value of the errors. Lower MAE indicates better prediction accuracy.

Leaderboard:

MODEL	AIC	BIC	RMSE	MSE	MAE
RNN	5288	8235	0.083619	0.006992	0.069909
CNN	71148	110012	0.119286	0.014229	0.112025
LSTM	61610	95270	0.124854	0.015588	0.103650
ARIMAX	1608	1613	959	920880	816
ARCH	1610	1618	2664	7099019.6894	2500
GARCH	1908	1919	2317	7331864	2273
ETS	1237	1282	3431	11777466	3301

The ETS (Exponential Smoothing) model excels in AIC (1237) and BIC (1282), which are metrics that favor simpler, more interpretable models. However, the RNN (Recurrent Neural Network) model stands out with significantly lower error rates, including the lowest RMSE (0.083619), MSE (0.006992), and MAE (0.069909). This indicates that the RNN model provides more accurate predictions overall. Despite the ETS model's advantages in terms of model simplicity and interpretability, the RNN's superior performance in error metrics suggests it would be a better choice for achieving higher predictive accuracy. Therefore, unless there is a strong preference for a simpler model, the RNN is recommended for its enhanced predictive performance.

CONCLUSION:

In this analysis, we have explored the interaction between key financial indicators: the S&P 500 Index (SPX), the INViXN Index, and the USD to INR exchange rate. Our objective was to predict the differences between these indices while accounting for the influence of exchange rate fluctuations. The data preprocessing, which included converting dates, handling missing values, and aggregating data, laid a solid foundation for our analysis.The time series visualizations and decomposition revealed a clear upward trend and significant volatility patterns, particularly in the INViXN Index, highlighting increased market uncertainty. Despite applying various transformations to achieve stationarity, the data remained non-stationary, suggesting complex underlying factors.The performance of different forecasting models was evaluated using metrics such as AIC, BIC, RMSE, MSE, and MAE. While the ETS (Exponential Smoothing) model demonstrated strong performance in AIC and BIC, favoring simplicity and interpretability, the RNN (Recurrent Neural Network) model excelled in minimizing prediction errors with the lowest RMSE, MSE, and MAE values.Overall, while the ETS model offers advantages in terms of model simplicity, the RNN model provides superior predictive accuracy. Hence, for improved forecasting precision and actionable insights, the RNN model is recommended. However, for scenarios where model simplicity and interpretability are crucial, the ETS model remains a valuable alternative.