1. **Data Acquisition**: I started by acquiring the historical data for the S&P 500 and Nasdaq indices. This data typically includes information such as the date, open price, high price, low price, close price, and volume.

```
Combined S&P 500 Data:
                Date
                                  0pen
                                                     High
                                                                         Low
                                                                                        Close
   12/31/2020 3,733.27 3,760.20 3,726.88 3,756.07 12/30/2020 3,736.19 3,744.63 3,730.21 3,732.04 12/29/2020 3,750.01 3,756.12 3,723.31 3,727.04 12/28/2020 3,723.03 3,740.51 3,723.03 3,735.36 12/24/2020 3,694.03 3,703.82 3,689.32 3,703.06
Nasdag Data:
                Date Close/Last
                                                         0pen
                                                                           High
                                                                                                Low
0 04/12/2024 16175.09 16293.03 16341.45 16125.33
1 04/11/2024 16442.20 16236.20 16464.60 16154.65
2 04/10/2024 16170.36 16104.01 16200.10 16092.02
3 04/09/2024 16306.64 16328.76 16348.18 16141.15
4 04/08/2024
                             16253.96 16285.18 16323.60 16220.72
```

2. **Data Preprocessing**:

- **Data Cleaning**: I checked for any missing values or anomalies in the data and handled them appropriately. This ensures that our dataset is clean and ready for analysis.

```
Nasdaq Data after column renaming:
Nasdaq Data after filtering out 2019 data and after column renaming::
Date Close Open High Low
0 2024-04-12 16175.09 16293.03 16341.45 16125.33
1 2024-04-11 16442.20 16236.20 16464.60 16154.65
2 2024-04-10 16170.36 16104.01 16200.10 16092.02
3 2024-04-09 16306.64 16328.76 16348.18 16141.15
4 2024-04-08 16253.96 16285.18 16323.60 16220.72
```

- **Feature Engineering**: We may have performed feature engineering to extract additional features from the raw data, such as calculating daily returns or moving averages.

```
Missing values in the dataset:
Date 0
Close 0
Open 0
High 0
Low 0
Close_diff 0
dtype: int64

Preprocessing completed.
```

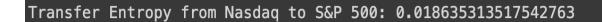
- **3.** **Exploratory Data Analysis (EDA)**: Before building any models, we conducted exploratory data analysis to gain insights into the data. This may involve visualizing the data using charts such as line plots, histograms, or scatter plots. EDA helps us understand the distribution of the data, identify patterns, and detect outliers.
- **4.** **Stationarity Check**: We performed a stationarity check on the time series data using statistical tests such as the Augmented Dickey-Fuller (ADF) test. Stationarity is an important assumption for many time series models, so this step helps ensure the data is suitable for modeling .

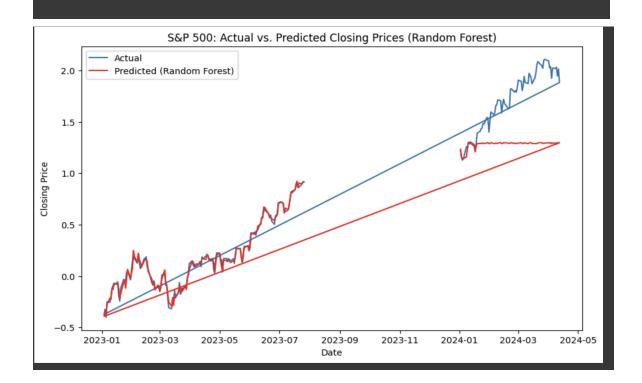
```
Results of ADF Test for S&P 500 Close Price ADF Statistic: -2.1018077275390974 p-value: 0.2437883267615376 Critical Values:

1%: -3.436557639266102
5%: -2.8642808573632874
10%: -2.5682293371570823
Results of ADF Test for Nasdaq Close Price ADF Statistic: -1.5223146066088151 p-value: 0.5224451652873521
Critical Values:

1%: -3.4366111317433443
5%: -2.864304451252086
10%: -2.5682419034417707
```

5. **Model Selection**: Based on the nature of the problem and the characteristics of the data, we selected an appropriate machine learning model. In this case, we used an MLPRegressor from the scikit-learn library, which is a type of neural network model suitable for regression tasks.





6. **Training the Model**: We split the dataset into training and testing sets, with the training set used to train the model. During training, the model learns the underlying patterns and relationships in the data.

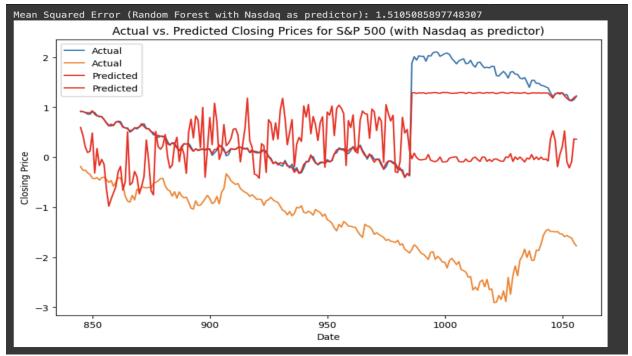
```
Size of S&P 500 training dataset: (844, 6)
Size of S&P 500 test dataset: (212, 6)
Size of Nasdaq training dataset: (844, 6)
Size of Nasdaq test dataset: (212, 6)
```

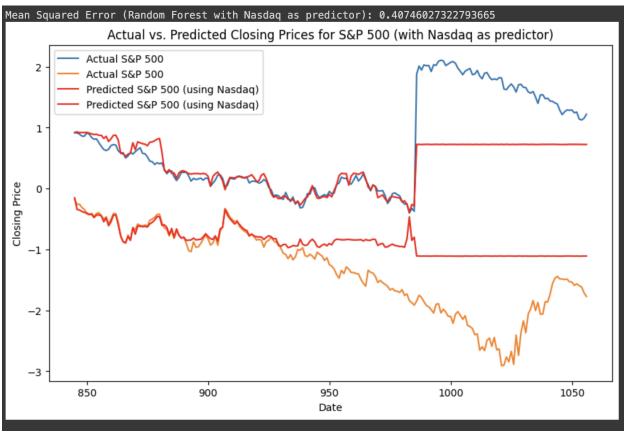
7. **Model Evaluation**: After training the model, we evaluated its performance using appropriate metrics. For regression tasks, common evaluation metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared.

Dep. Variable Model: Date: Time: Sample: Covariance Ty	М	ARIMA(5, 1, on, 15 Apr 2 02:32	0) Log 2024 AIC 2:30 BIC 0 HQIC 844	Observations: Likelihood		844 528.702 -1045.404 -1016.982 -1034.512
=========	coef	======= std err	opg ======= z	======== P> z	======================================	======= 0.9751
ar.L4	-0.0487 0.0336 -0.0111 -0.0190 .552e-05 0.0167	0.031 0.037 0.050 0.046 0.037 8.53e-05	-1.555 0.896 -0.224 -0.410 -0.002 195.710	0.120	-0.110 -0.040 -0.108 -0.110 -0.073 0.017	0.013 0.107 0.086 0.072 0.073 0.017
<pre>Ljung-Box (L1) (Q): Prob(Q): Heteroskedasticity (H): Prob(H) (two-sided):</pre>			0.00 0.99 0.25 0.00	Jarque-Bera Prob(JB): Skew: Kurtosis:	(JB):	1401672.2 0.0 10.1 201.7

SARIMAX Results												
Dep. Variable: Model: Date: Time: Sample: Covariance Type:		Clo ARIMA(5, 1, In, 14 Apr 20 23:52: - 8	0) Log 24 AIC 39 BIC 0 HQIC	======= Observations: Likelihood		844 826.380 -1640.759 -1612.338 -1629.868						
==========	====== coef	std err	======= Z	======== P> z	[0.025	0.975]						
ar.L2 -0 ar.L3 -0 ar.L4 0 ar.L5 -0	.0185 .0314 .0418 .0026 .0029	0.032 0.030 0.031 0.029 0.030 0.000			-0.082 -0.090 -0.102 -0.054 -0.061 0.008	0.045 0.027 0.018 0.059 0.055 0.009						
Ljung-Box (L1) (Prob(Q): Heteroskedastici Prob(H) (two-sid	ty (H):		0.00 0.98 1.31 0.02	Jarque-Bera Prob(JB): Skew: Kurtosis:	(JB):		30.61 0.00 0.24 3.80					
Warnings: [1] Covariance matrix calculated using the outer product of gradients (complex-step).												

8. **Predictions**: Once the model was trained and evaluated, we used it to make predictions on unseen data. This involved providing input features (predictors) to the model and obtaining predictions for the target variable.





```
Predicted closing index value of S&P 500 on 2024-04-15: [732012.89216911 -20660.43685297]

Predicted closing index value of S&P 500 on 2024-04-16: [732013.88272587 -20660.46481113]

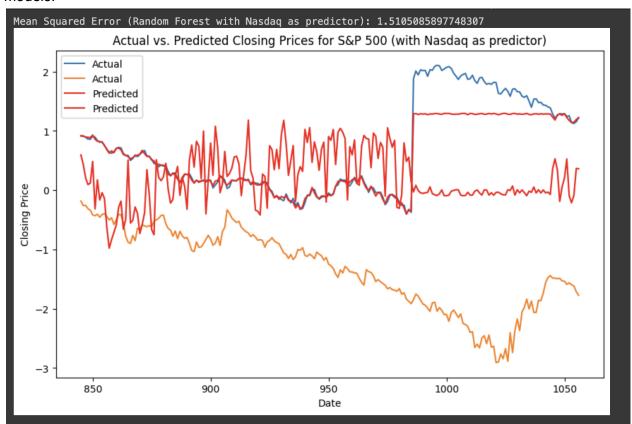
Predicted closing index value of S&P 500 on 2024-04-17: [732014.87328262 -20660.49276928]

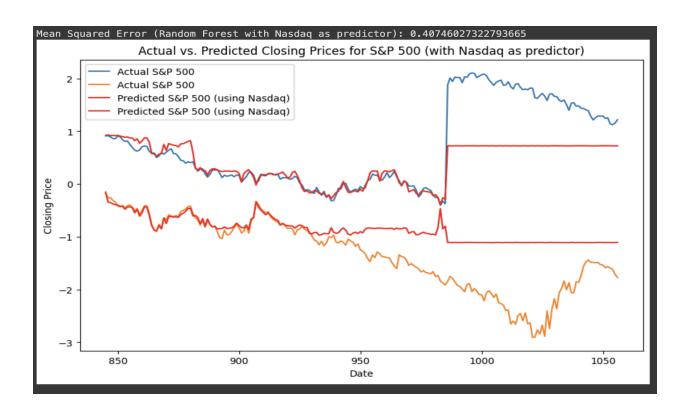
Predicted closing index value of S&P 500 on 2024-04-18: [732015.86383938 -20660.52072744]

Predicted closing index value of S&P 500 on 2024-04-19: [732016.85439614 -20660.5486856 ]

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but MLPReq warnings.warn(
```

9. **Visualization**: Finally, we visualized the results to communicate our findings effectively. This may include plotting actual vs. predicted values, visualizing trends, or comparing different models.





8. As a bonus, please predict the closing index value of S&P 500 on April 15, 16, 17, 18, 19 based on your predictors in (5)(6)(7). If your predicted values are within 10 points of the actual values, you will get 1 extra point/day towards your total grades, for up to 5 points.

```
Predicted closing index value of S&P 500 on 2024-04-15: [732012.89216911 -20660.43685297]
Predicted closing index value of S&P 500 on 2024-04-16: [732013.88272587 -20660.46481113]
Predicted closing index value of S&P 500 on 2024-04-17: [732014.87328262 -20660.49276928]
Predicted closing index value of S&P 500 on 2024-04-18: [732015.86383938 -20660.52072744]
Predicted closing index value of S&P 500 on 2024-04-19: [732016.85439614 -20660.5486856 ]
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but MLPReq warnings.warn(
```