StockMarketPredictionUsingML

November 5, 2022

1 Visualizing and Forecasting of Stocks (NSE)

- `Pandas` – This library helps to load the data frame in a 2D array format and has multiple functions to perform analysis tasks in one go.
- `Numpy` – Numpy arrays are very fast and can perform large computations in a very short time.
- `Matplotlib/Seaborn` – This library is used to draw visualizations.
- `Sklearn` – This module contains multiple libraries having pre-implemented functions to perform tasks from data preprocessing to model development and evaluation.
- `XGBoost` – This contains the eXtreme Gradient Boosting machine learning algorithm which is one of the algorithms which helps us to achieve high accuracy on predictions.

[1]:
```python
#importing the libraries
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd
from pandas.plotting import lag_plot
import glob
import os
sns.set()
import warnings
warnings.filterwarnings('ignore')

import chart_studio.plotly as py
import plotly.graph_objs as go
from plotly.offline import plot
import seaborn as sb
#for offline plotting
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)

import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn import metrics
```

1.1 Importing Dataset

- The dataset we will use here to perform the analysis and build a predictive model is Adani Enterprise Stock Price data.
- We will use OHLC('Open', 'High', 'Low', 'Close') data from 1st January 2019 to 3rd Nov 2022

[2]:
```
#loading the data
adanient = pd.read_csv('NSE_ADANIENT.csv',parse_dates=['Date'], dayfirst=True)
#adanient['Date'] = pd.to_datetime(adanient['Date'])
adanient.head()
```

[2]:
```
        Date        Open        High         Low       Close   Adj Close  \
0 2019-01-01  160.899994  162.350006  155.449997  157.250000  155.465088
1 2019-01-02  157.000000  157.850006  152.500000  154.850006  153.092361
2 2019-01-03  154.899994  156.100006  150.300003  152.500000  150.769012
3 2019-01-04  152.100006  154.000000  150.000000  152.550003  150.818451
4 2019-01-07  152.899994  154.449997  150.250000  151.250000  149.533203

    Volume
0  4726656
1  2735262
2  2758876
3  2777308
4  2714218
```

- From the first five rows, we can see that data for some of the dates is missing the reason for that is on weekends and holidays Stock Market remains closed hence no trading happens on these days.

[3]:
```
adanient.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 950 entries, 0 to 949
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       950 non-null    datetime64[ns]
 1   Open       950 non-null    float64
 2   High       950 non-null    float64
 3   Low        950 non-null    float64
 4   Close      950 non-null    float64
 5   Adj Close  950 non-null    float64
 6   Volume     950 non-null    int64
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 52.1 KB
```

[4]:
```
print("\n")
```

```
print("Open   --- mean :", np.mean(adanient['Open']),  "  \t Std: ", np.
 ↪std(adanient['Open']),  "  \t Max: ", np.max(adanient['Open']),  "  \t Min:␣
 ↪", np.min(adanient['Open']))
print("High   --- mean :", np.mean(adanient['High']),  "  \t Std: ", np.
 ↪std(adanient['High']),  "  \t Max: ", np.max(adanient['High']),  "  \t Min:␣
 ↪", np.min(adanient['High']))
print("Low    --- mean :", np.mean(adanient['Low']),   "  \t Std: ", np.
 ↪std(adanient['Low']),   "  \t Max: ", np.max(adanient['Low']),   "  \t Min:␣
 ↪", np.min(adanient['Low']))
print("Close  --- mean :", np.mean(adanient['Close']), "  \t Std: ", np.
 ↪std(adanient['Close']), "  \t Max: ", np.max(adanient['Close']), "  \t Min:␣
 ↪", np.min(adanient['Close']))
print("Volume --- mean :", np.mean(adanient['Volume']),"  \t Std: ", np.
 ↪std(adanient['Volume']),"  \t Max: ", np.max(adanient['Volume']),"  \t Min:␣
 ↪", np.min(adanient['Volume']))
```

```
Open   --- mean : 967.6365255178948      Std:  959.4566600451187         Max:
3837.649902          Min:  116.349998
High   --- mean : 986.2366821631572      Std:  975.2937875729492         Max:
3885.0               Min:  119.5
Low    --- mean : 949.9067905957897      Std:  943.5604917335505         Max:
3812.0               Min:  113.0
Close  --- mean : 969.0835262031584      Std:  960.392715442575          Max:
3834.550049          Min:  116.949997
Volume --- mean : 4898751.874736842      Std:  5184593.824054264         Max:
61334483             Min:  248249
```

[5]:
```
adanient.shape
```

[5]:
```
(950, 7)
```

- From this, we got to know that there are 950 rows of data available and for each row, we have 7 different features or columns.

[6]:
```
adanient['Date'] = pd.to_datetime(adanient['Date'])
```

[7]:
```
print(f'Dataframe contains stock prices between {adanient.Date.min()} {adanient.
 ↪Date.max()}')
print(f'Total days = {(adanient.Date.max()  - adanient.Date.min()).days} days')
```

```
Dataframe contains stock prices between 2019-01-01 00:00:00 2022-11-03 00:00:00
Total days = 1402 days
```

[8]:
```
adanient.describe()
```

[8]:
```
                Open         High          Low        Close    Adj Close  \
count   950.000000   950.000000   950.000000   950.000000   950.000000
mean    967.636526   986.236682   949.906791   969.083526   968.184123
std     959.962036   975.807506   944.057495   960.898585   961.141005
min     116.349998   119.500000   113.000000   116.949997   115.622528
25%     154.000000   157.037506   150.250000   153.162495   152.074284
50%     437.100006   454.399994   418.725006   446.600006   446.114136
75%    1632.562500  1669.462463  1608.412537  1644.287476  1643.588806
max    3837.649902  3885.000000  3812.000000  3834.550049  3834.550049

             Volume
count  9.500000e+02
mean   4.898752e+06
std    5.187325e+06
min    2.482490e+05
25%    2.156603e+06
50%    3.549359e+06
75%    5.559366e+06
max    6.133448e+07
```

[9]:
```
adanient.isnull().sum()
```

[9]:
```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

[10]:
```
adanient =adanient.dropna()
```

[11]:
```
adanient.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 950 entries, 0 to 949
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       950 non-null    datetime64[ns]
 1   Open       950 non-null    float64
 2   High       950 non-null    float64
 3   Low        950 non-null    float64
 4   Close      950 non-null    float64
 5   Adj Close  950 non-null    float64
 6   Volume     950 non-null    int64
dtypes: datetime64[ns](1), float64(5), int64(1)
```

```
memory usage: 52.1 KB
```

[12]:
```python
adanient.shape
```

[12]:
```
(950, 7)
```

- checking the the null values if any are present in the data frame.

[13]:
```python
adanient.isnull().sum()
```

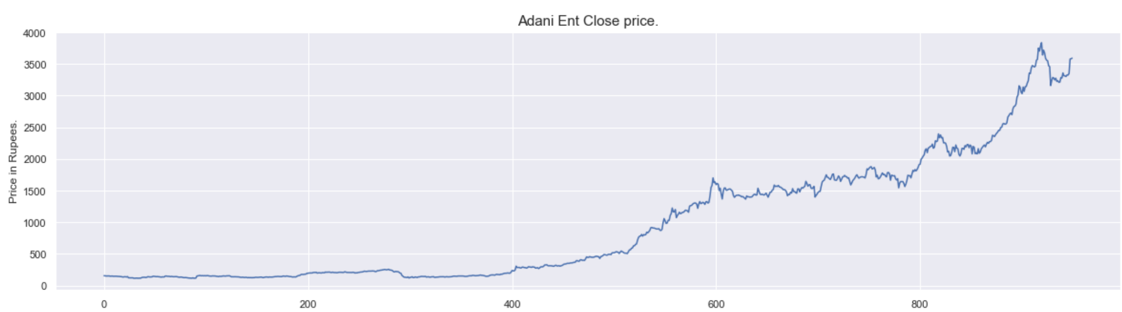
[13]:
```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

- This implies that there are no null values in the data set provided.

1.2 Exploratory Data Analysis

- EDA is an approach to analyzing the data using visual techniques. It is used to discover trends, and patterns, or to check assumptions with the help of statistical summaries and graphical representations.
- While performing the EDA of the Adani Enterprise Stock Price data we will analyze how prices of the stock have moved over the period of time and how the end of the quarters affects the prices of the stock.

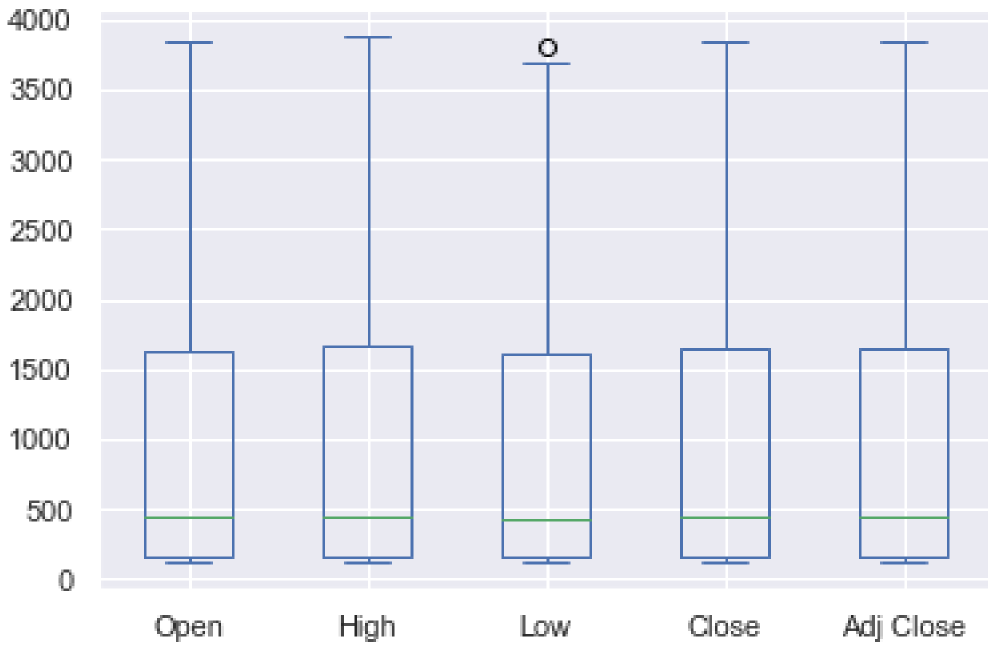
[14]:
```python
plt.figure(figsize=(20,5))
plt.plot(adanient['Close'])
plt.title('Adani Ent Close price.', fontsize=15)
plt.ylabel('Price in Rupees.')
plt.show()
```



The prices of the `Adani Ent` stocks are showing an upward trend as depicted by the plot of the closing price of the stocks

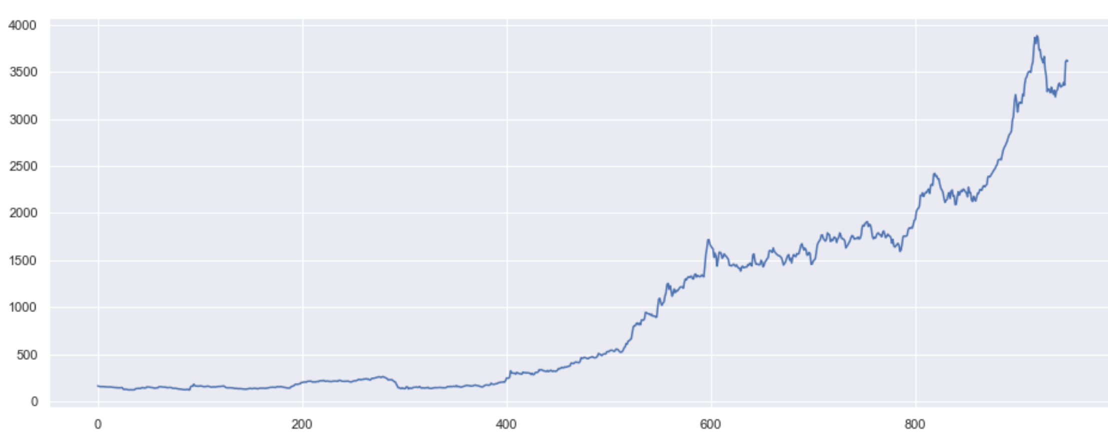
[15]:
```
adanient[['Open','High','Low','Close','Adj Close']].plot(kind='box')
```

[15]: <AxesSubplot:>



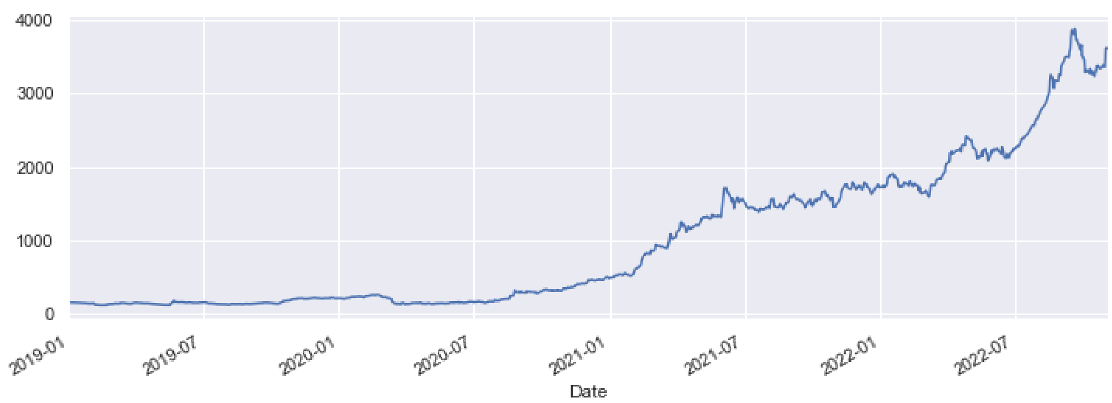
[16]:
```
adanient['High'].plot(figsize=(16,6))
```

[16]: <AxesSubplot:>



[17]:
```
adanient=adanient.set_index('Date',drop=True) # yarra added we can remove later␣
 ↪for testing purpose
## xlimit and y limit
adanient['High'].plot(xlim=['2019-01-01','2022-11-04'],figsize=(12,4))
```

[17]:
```
<AxesSubplot:xlabel='Date'>
```



[18]:
```
adanient.index
```

[18]:
```
DatetimeIndex(['2019-01-01', '2019-01-02', '2019-01-03', '2019-01-04',
               '2019-01-07', '2019-01-08', '2019-01-09', '2019-01-10',
               '2019-01-11', '2019-01-14',
               …
               '2022-10-20', '2022-10-21', '2022-10-24', '2022-10-25',
               '2022-10-27', '2022-10-28', '2022-10-31', '2022-11-01',
               '2022-11-02', '2022-11-03'],
              dtype='datetime64[ns]', name='Date', length=950, freq=None)
```

[19]:
```
index=adanient.loc['2019-01-01':'2022-11-01'].index
share_open=adanient.loc['2019-01-01':'2022-11-01']['Open']
```

[20]:
```
share_open
```

[20]:
```
Date
2019-01-01     160.899994
2019-01-02     157.000000
2019-01-03     154.899994
2019-01-04     152.100006
2019-01-07     152.899994
                  …
2022-10-25    3321.949951
2022-10-27    3319.850098
2022-10-28    3322.000000
```

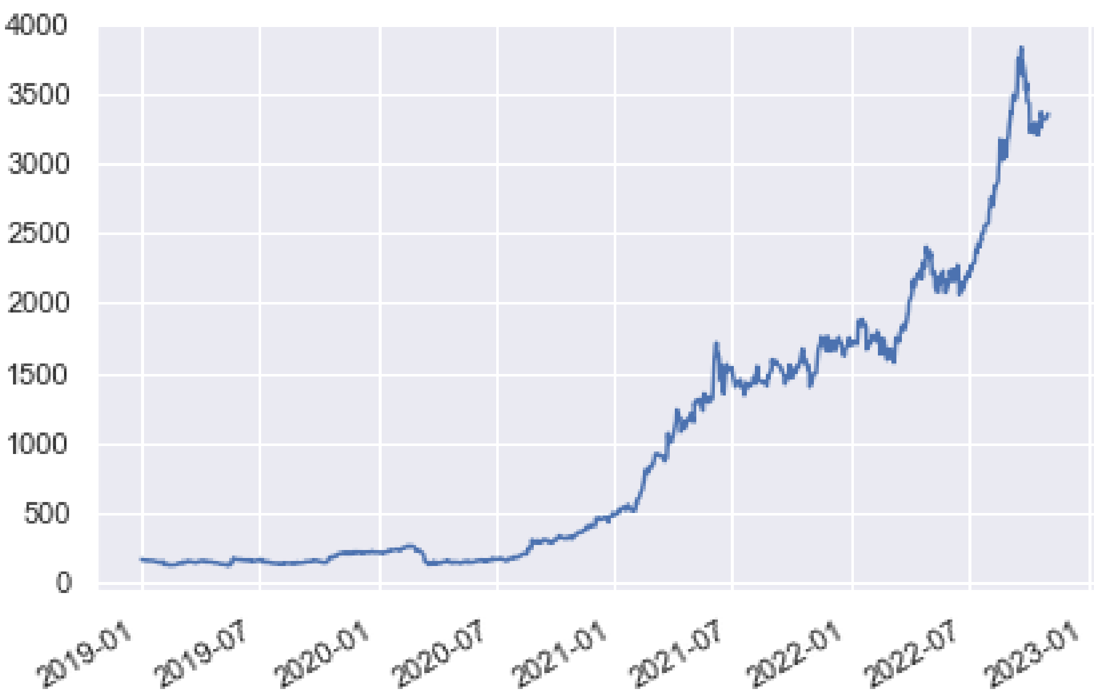
```
2022-10-31    3339.949951
2022-11-01    3361.899902
Name: Open, Length: 948, dtype: float64
```

[21]:
```
index
```

[21]:
```
DatetimeIndex(['2019-01-01', '2019-01-02', '2019-01-03', '2019-01-04',
               '2019-01-07', '2019-01-08', '2019-01-09', '2019-01-10',
               '2019-01-11', '2019-01-14',
               …
               '2022-10-18', '2022-10-19', '2022-10-20', '2022-10-21',
               '2022-10-24', '2022-10-25', '2022-10-27', '2022-10-28',
               '2022-10-31', '2022-11-01'],
              dtype='datetime64[ns]', name='Date', length=948, freq=None)
```

[22]:
```
figure,axis=plt.subplots()
plt.tight_layout()
## Preventing overlapping
figure.autofmt_xdate()
axis.plot(index,share_open)
```

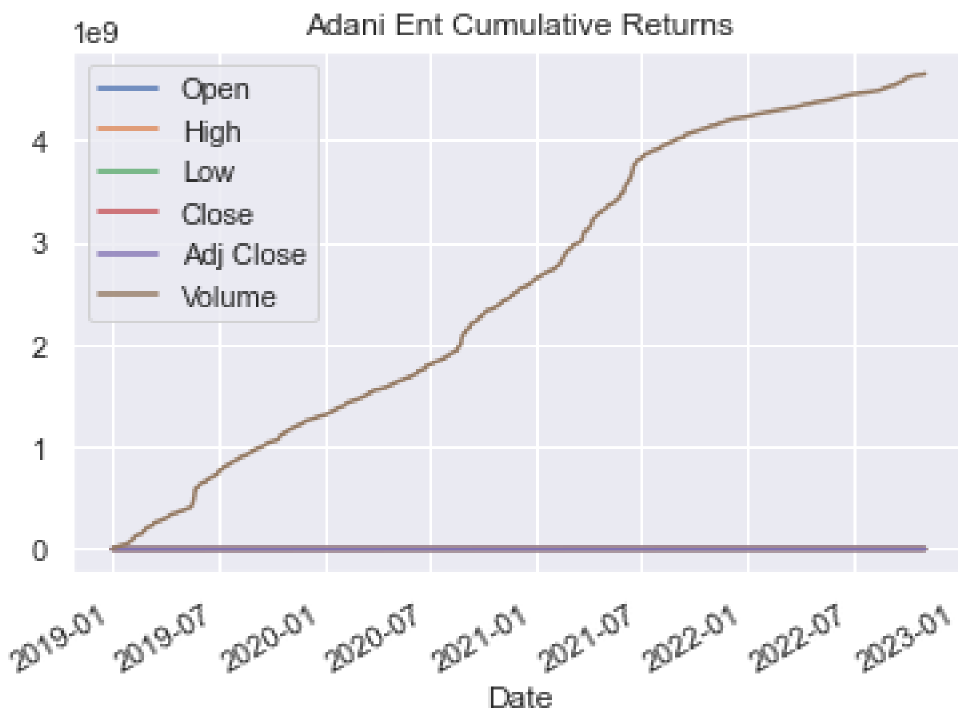
[22]:
```
[<matplotlib.lines.Line2D at 0x18e11c7c6a0>]
```



[23]:
```
adanient[['Close']].plot()
plt.title("Adani Ent")
plt.show()
```

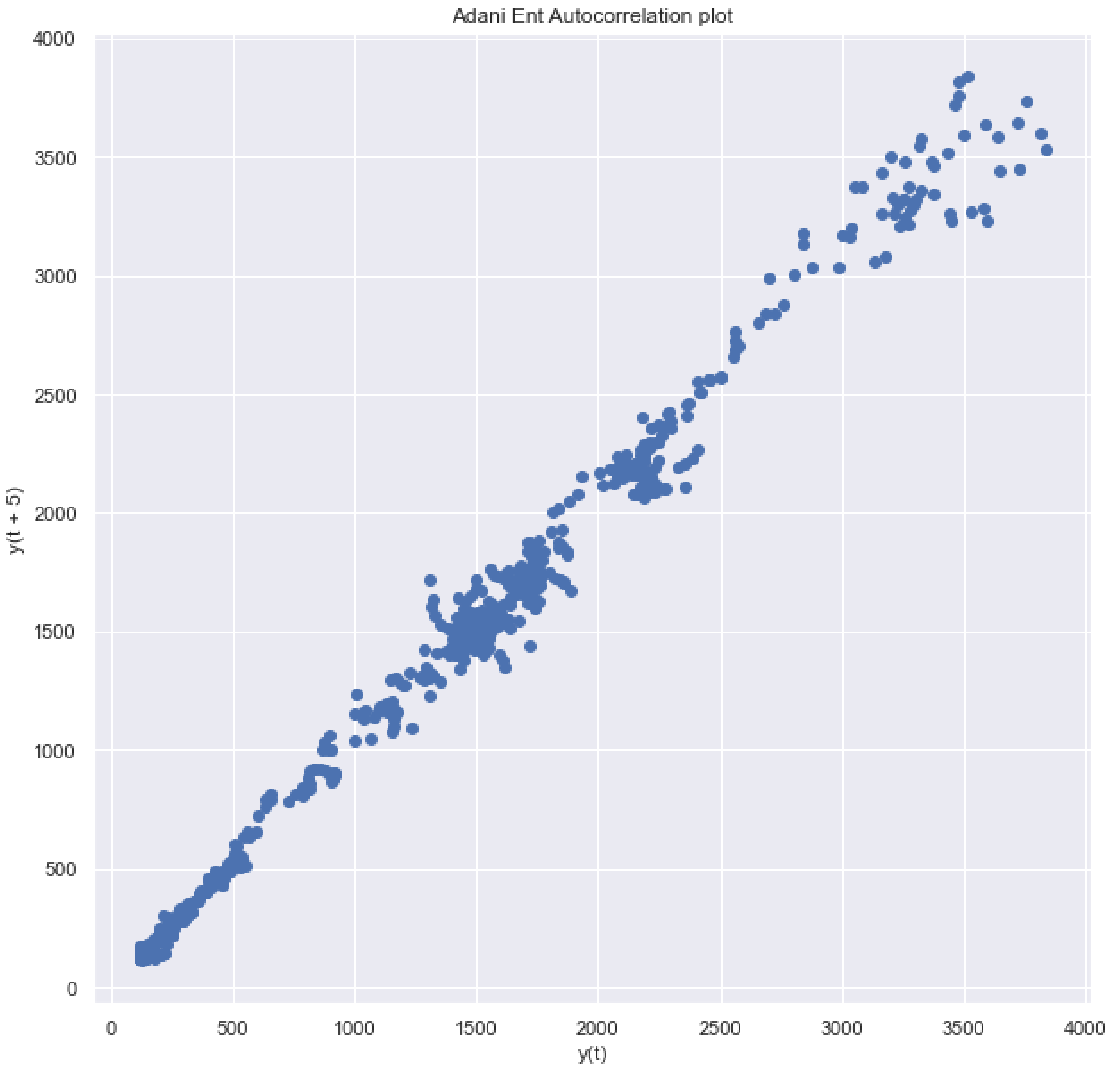
[24]:
```
# Comulative Return
dr = adanient.cumsum()
dr.plot()
plt.title('Adani Ent Cumulative Returns')
```

[24]:
```
Text(0.5, 1.0, 'Adani Ent Cumulative Returns')
```



[25]:
```
plt.figure(figsize=(10,10))
lag_plot(adanient['Open'], lag=5)
plt.title('Adani Ent Autocorrelation plot')
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
*x* & *y*.  Please use the *color* keyword-argument or provide a 2D array with a
single row if you intend to specify the same RGB or RGBA value for all points.
```



[26]:
```
adanient=adanient.reset_index()
```

[27]:
```
adanient.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 950 entries, 0 to 949
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       950 non-null    datetime64[ns]
 1   Open       950 non-null    float64
 2   High       950 non-null    float64
 3   Low        950 non-null    float64
 4   Close      950 non-null    float64
 5   Adj Close  950 non-null    float64
```

```
 6   Volume     950 non-null    int64
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 52.1 KB
```

[28]:
```
adanient=adanient.set_index('Date',drop=True)
```

[29]:
```
adanient.head()
```

[29]:
```
                  Open        High         Low       Close   Adj Close  \
Date
2019-01-01  160.899994  162.350006  155.449997  157.250000  155.465088
2019-01-02  157.000000  157.850006  152.500000  154.850006  153.092361
2019-01-03  154.899994  156.100006  150.300003  152.500000  150.769012
2019-01-04  152.100006  154.000000  150.000000  152.550003  150.818451
2019-01-07  152.899994  154.449997  150.250000  151.250000  149.533203

             Volume
Date
2019-01-01  4726656
2019-01-02  2735262
2019-01-03  2758876
2019-01-04  2777308
2019-01-07  2714218
```

[30]:
```
## datetime
from datetime import datetime
```

1.3 Time Resampling

[31]:
```
adanient.resample(rule='A').min()
```

[31]:
```
                   Open         High          Low        Close    Adj Close  \
Date
2019-12-31   116.349998   119.500000   113.000000   116.949997   115.622528
2020-12-31   121.000000   129.800003   116.400002   120.900002   120.768463
2021-12-31   477.000000   493.250000   477.000000   490.899994   490.365906
2022-12-31  1574.900024  1592.000000  1528.800049  1543.949951  1543.293945

             Volume
Date
2019-12-31  1003411
2020-12-31   620753
2021-12-31   272261
2022-12-31   248249
```

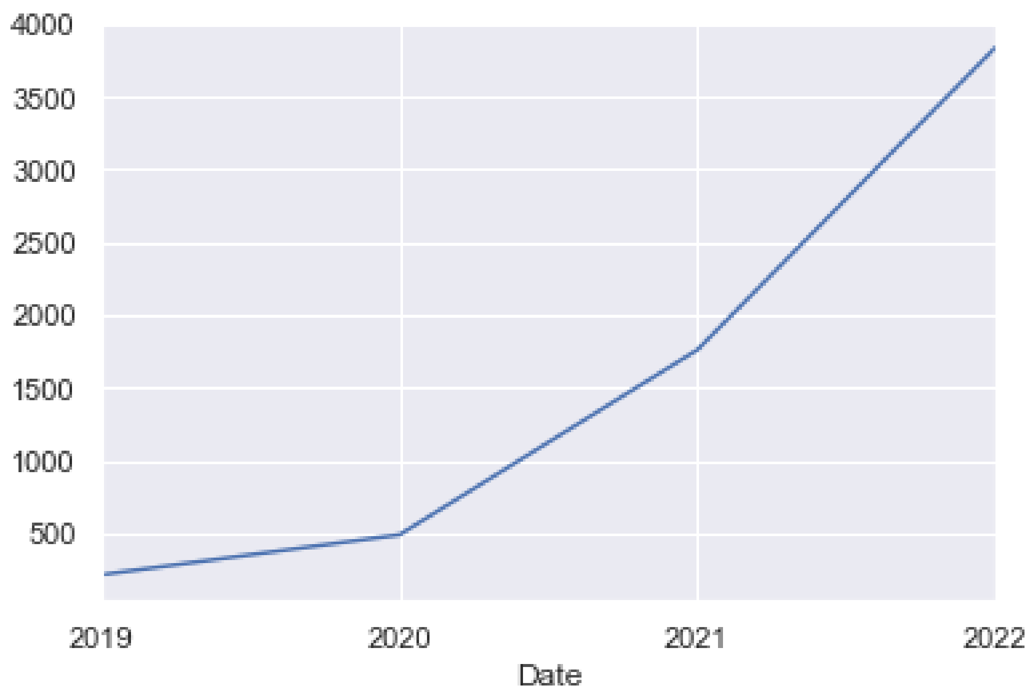
[32]:
```
adanient.resample(rule='A').max()
```

[32]:

```
                  Open         High          Low        Close    Adj Close  \
Date
2019-12-31   217.750000   221.500000   212.399994   218.800003   216.974716
2020-12-31   492.000000   507.000000   484.700012   490.850006   490.315948
2021-12-31  1762.949951  1788.900024  1735.550049  1763.050049  1762.300903
2022-12-31  3837.649902  3885.000000  3812.000000  3834.550049  3834.550049

              Volume
Date
2019-12-31  61334483
2020-12-31  49264537
2021-12-31  43530006
2022-12-31  15060223
```

[33]:

```
##year end frequency
adanient.resample(rule='A').max()['Open'].plot()
plt.show()
```

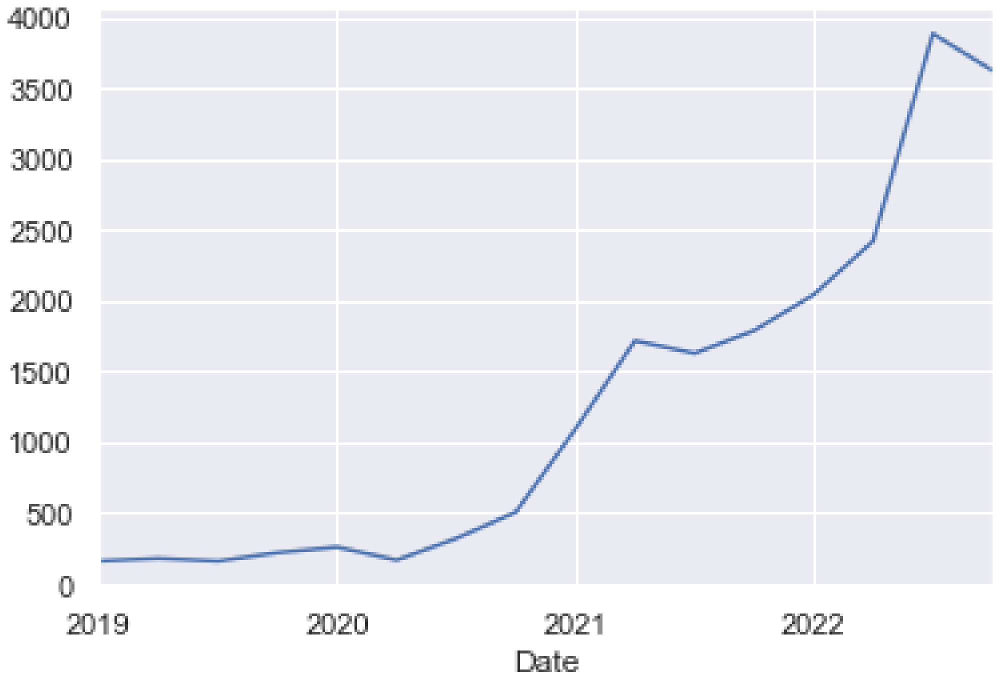


- We are downsample the data using the alias "A" for year-end frequency for `Open` column and plot results in plot

[34]:

```
##quaterly start frequency
##https://towardsdatascience.com/resample-function-of-pandas-79b17ec82a78
adanient.resample(rule='QS').max()['High'].plot()
```

[34]: <AxesSubplot:xlabel='Date'>



- We are downsample the data using the alias "A" for Quaterly starting data frequency for High column and plot results in plot

[35]:
```
##Business End Frequency
##https://towardsdatascience.com/resample-function-of-pandas-79b17ec82a78
adanient.resample(rule='BA').max()
```

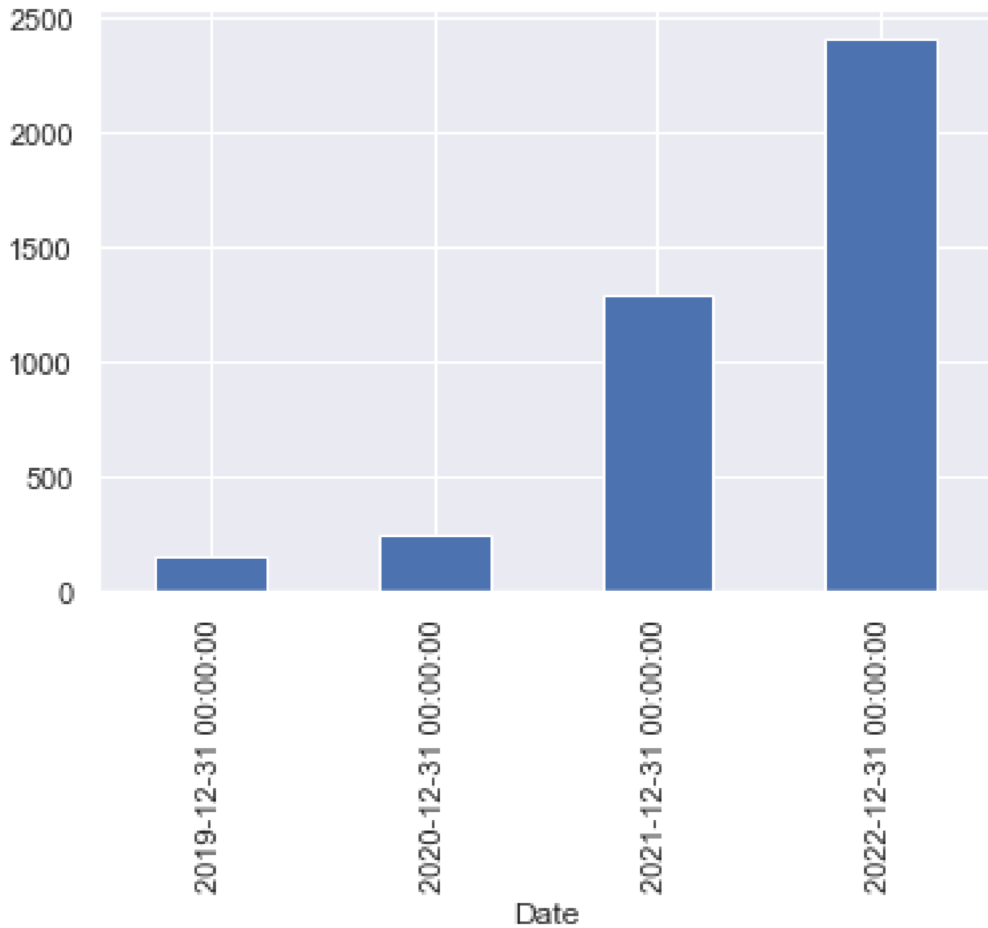
[35]:
```
                   Open         High          Low        Close    Adj Close  \
Date
2019-12-31   217.750000   221.500000   212.399994   218.800003   216.974716
2020-12-31   492.000000   507.000000   484.700012   490.850006   490.315948
2021-12-31  1762.949951  1788.900024  1735.550049  1763.050049  1762.300903
2022-12-30  3837.649902  3885.000000  3812.000000  3834.550049  3834.550049

              Volume
Date
2019-12-31  61334483
2020-12-31  49264537
2021-12-31  43530006
2022-12-30  15060223
```

[36]:
```
adanient.resample(rule='BQS').max()
```

[36]:
```
                   Open         High          Low        Close    Adj Close  \
Date
2019-01-01   160.899994   162.350006   155.449997   157.250000   155.465088
2019-04-01   169.500000   180.800003   157.699997   161.050003   159.221970
2019-07-01   160.100006   161.800003   154.300003   156.100006   154.328156
2019-10-01   217.750000   221.500000   212.399994   218.800003   216.974716
2020-01-01   256.899994   261.000000   252.649994   258.649994   256.492279
2020-04-01   164.000000   169.199997   161.300003   162.149994   161.973587
2020-07-01   301.799988   322.399994   295.100006   307.549988   307.215393
2020-10-01   492.000000   507.000000   484.700012   490.850006   490.315948
2021-01-01  1063.000000  1093.000000  1018.400024  1058.400024  1057.248535
2021-04-01  1715.000000  1717.199951  1613.000000  1700.949951  1699.099365
2021-07-01  1594.900024  1628.449951  1566.050049  1587.599976  1586.925415
2021-10-01  1762.949951  1788.900024  1735.550049  1763.050049  1762.300903
2022-01-03  2005.000000  2042.000000  1991.000000  2014.750000  2013.893921
2022-04-01  2404.949951  2420.949951  2336.300049  2395.300049  2394.282227
2022-07-01  3837.649902  3885.000000  3812.000000  3834.550049  3834.550049
2022-10-03  3580.000000  3625.149902  3542.449951  3590.399902  3590.399902

              Volume
Date
2019-01-01  14695085
2019-04-01  61334483
2019-07-01  15687573
2019-10-01  14162661
2020-01-01  10810744
2020-04-01  16533100
2020-07-01  49264537
2020-10-01  20009492
2021-01-01  31098225
2021-04-01  43530006
2021-07-01  14250256
2021-10-01   7093354
2022-01-03   5126019
2022-04-01   6515102
2022-07-01  15060223
2022-10-03   7578847
```

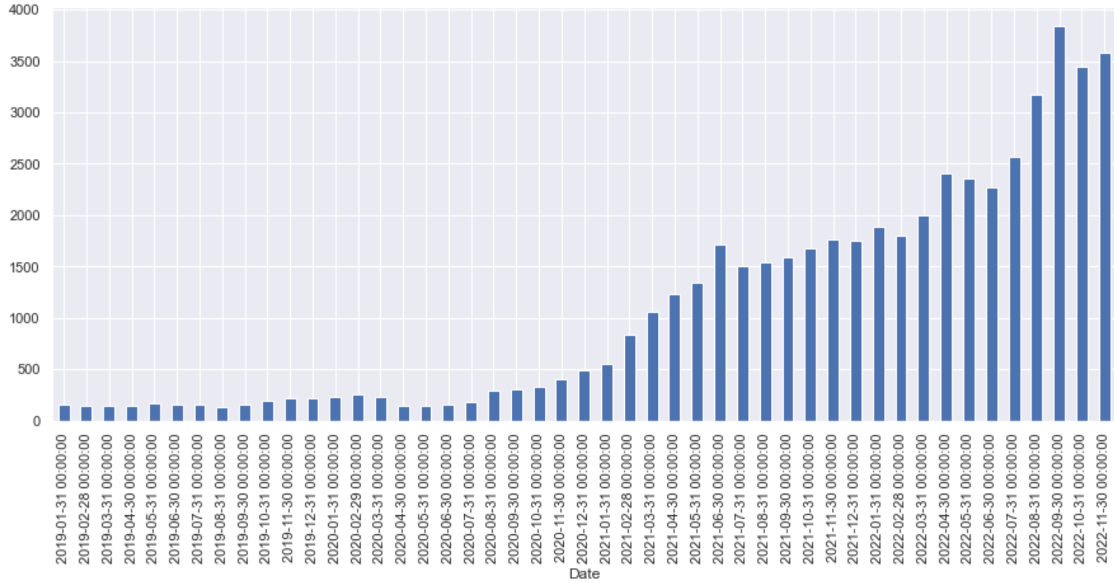
[37]:
```python
##plotting
adanient['Open'].resample(rule='A').mean().plot(kind='bar')
```

[37]: <AxesSubplot:xlabel='Date'>



[38]:
```
adanient['Open'].resample(rule='M').max().plot(kind='bar',figsize=(15,6))
```

[38]: <AxesSubplot:xlabel='Date'>



[39]:
```
adanient['High'].rolling(11).max().head(20)
```

[39]:
```
Date
2019-01-01           NaN
2019-01-02           NaN
2019-01-03           NaN
2019-01-04           NaN
2019-01-07           NaN
2019-01-08           NaN
2019-01-09           NaN
2019-01-10           NaN
2019-01-11           NaN
2019-01-14           NaN
2019-01-15    162.350006
2019-01-16    157.850006
2019-01-17    156.100006
2019-01-18    154.449997
2019-01-21    154.449997
2019-01-22    154.449997
2019-01-23    154.449997
2019-01-24    152.600006
2019-01-25    152.600006
2019-01-28    151.250000
Name: High, dtype: float64
```

[40]:
```
adanient.head()
```

[40]:
```
                  Open        High         Low       Close   Adj Close  \
Date
2019-01-01  160.899994  162.350006  155.449997  157.250000  155.465088
2019-01-02  157.000000  157.850006  152.500000  154.850006  153.092361
2019-01-03  154.899994  156.100006  150.300003  152.500000  150.769012
2019-01-04  152.100006  154.000000  150.000000  152.550003  150.818451
2019-01-07  152.899994  154.449997  150.250000  151.250000  149.533203

             Volume
Date
2019-01-01  4726656
2019-01-02  2735262
2019-01-03  2758876
2019-01-04  2777308
2019-01-07  2714218
```

[41]:
```python
adanient['Open:30 days rolling']=adanient['Open'].rolling(30).mean()
```

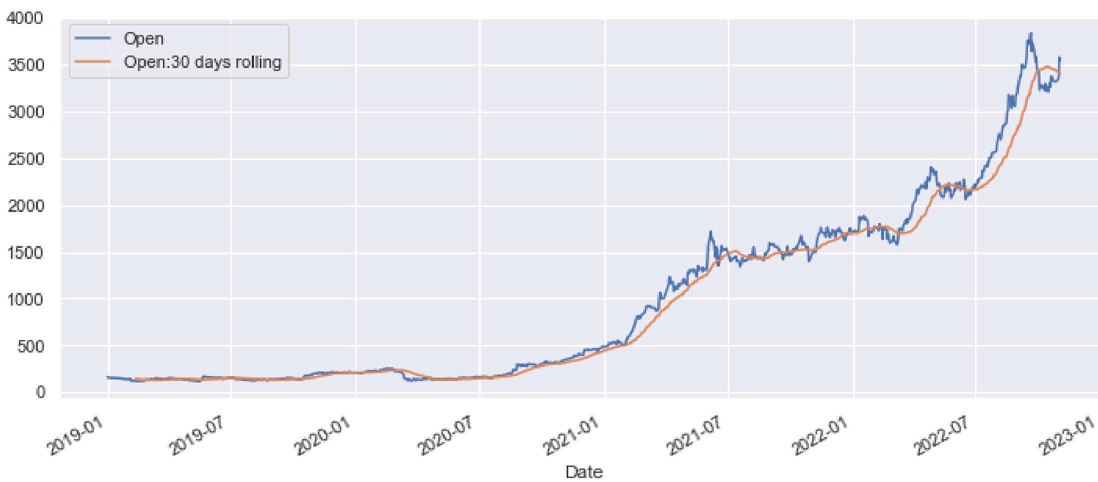
[42]:
```python
adanient.head(31)
```

[42]:
```
                  Open        High         Low       Close   Adj Close  \
Date
2019-01-01  160.899994  162.350006  155.449997  157.250000  155.465088
2019-01-02  157.000000  157.850006  152.500000  154.850006  153.092361
2019-01-03  154.899994  156.100006  150.300003  152.500000  150.769012
2019-01-04  152.100006  154.000000  150.000000  152.550003  150.818451
2019-01-07  152.899994  154.449997  150.250000  151.250000  149.533203
2019-01-08  150.500000  154.300003  149.649994  153.449997  151.708237
2019-01-09  153.600006  154.449997  147.600006  149.350006  147.654785
2019-01-10  151.000000  151.800003  148.500000  151.100006  149.384918
2019-01-11  151.100006  152.600006  149.100006  151.500000  149.780380
2019-01-14  151.000000  151.149994  147.000000  148.350006  146.666122
2019-01-15  148.500000  149.949997  147.250000  148.649994  146.962708
2019-01-16  148.199997  150.699997  148.000000  148.449997  146.764984
2019-01-17  148.399994  151.250000  146.350006  149.000000  147.308746
2019-01-18  149.699997  149.800003  144.550003  146.750000  145.084274
2019-01-21  146.500000  148.000000  144.250000  145.949997  144.293365
2019-01-22  145.399994  146.649994  141.699997  145.699997  144.046219
2019-01-23  145.500000  146.500000  142.050003  143.000000  141.376846
2019-01-24  143.000000  144.050003  141.100006  142.550003  140.931961
2019-01-25  142.850006  145.449997  136.149994  137.350006  135.790985
2019-01-28  138.000000  141.000000  118.949997  136.399994  134.851761
2019-01-29  136.449997  143.800003  133.600006  140.800003  139.201828
2019-01-30  140.899994  141.500000  136.500000  139.899994  138.312027
2019-01-31  139.500000  141.750000  135.000000  137.149994  135.593246
2019-02-01  136.949997  144.800003  134.550003  143.000000  141.376846
2019-02-04  142.899994  142.899994  121.300003  123.099998  121.702728
```

```
2019-02-05  122.000000  127.400002  119.599998  124.250000  122.839676
2019-02-06  123.849998  124.199997  114.800003  122.900002  121.505005
2019-02-07  122.199997  126.800003  119.050003  123.949997  122.543083
2019-02-08  123.000000  125.449997  115.699997  123.750000  122.345345
2019-02-11  122.949997  123.250000  115.800003  118.199997  116.858345
2019-02-12  117.199997  120.000000  115.349998  116.949997  115.622528

             Volume  Open:30 days rolling
Date
2019-01-01  4726656                   NaN
2019-01-02  2735262                   NaN
2019-01-03  2758876                   NaN
2019-01-04  2777308                   NaN
2019-01-07  2714218                   NaN
2019-01-08  2791866                   NaN
2019-01-09  4054809                   NaN
2019-01-10  3534546                   NaN
2019-01-11  2254999                   NaN
2019-01-14  2624582                   NaN
2019-01-15  1805678                   NaN
2019-01-16  1574176                   NaN
2019-01-17  2618859                   NaN
2019-01-18  2306520                   NaN
2019-01-21  1763205                   NaN
2019-01-22  2261667                   NaN
2019-01-23  2322990                   NaN
2019-01-24  1678843                   NaN
2019-01-25  3297651                   NaN
2019-01-28  9404485                   NaN
2019-01-29  4301493                   NaN
2019-01-30  3102926                   NaN
2019-01-31  3498642                   NaN
2019-02-01  7091209                   NaN
2019-02-04  9832462                   NaN
2019-02-05  8484607                   NaN
2019-02-06  9905219                   NaN
2019-02-07  9826247                   NaN
2019-02-08  8059813                   NaN
2019-02-11  7048335            143.391665
2019-02-12  3698931            141.934999
```

[43]:
```
adanient[['Open','Open:30 days rolling']].plot(figsize=(12,5))
```

[43]: <AxesSubplot:xlabel='Date'>

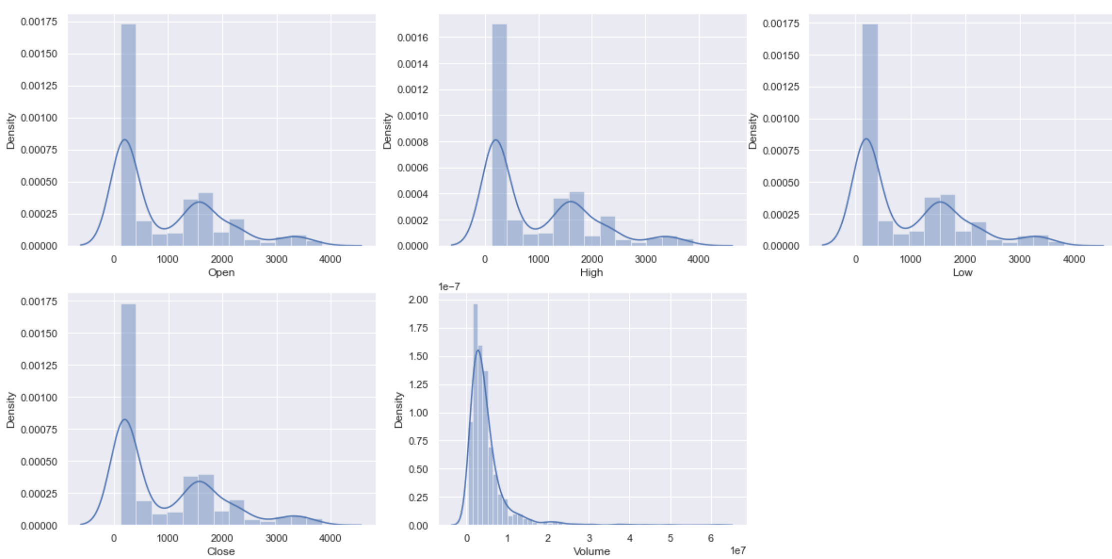


[ ]:

```

```

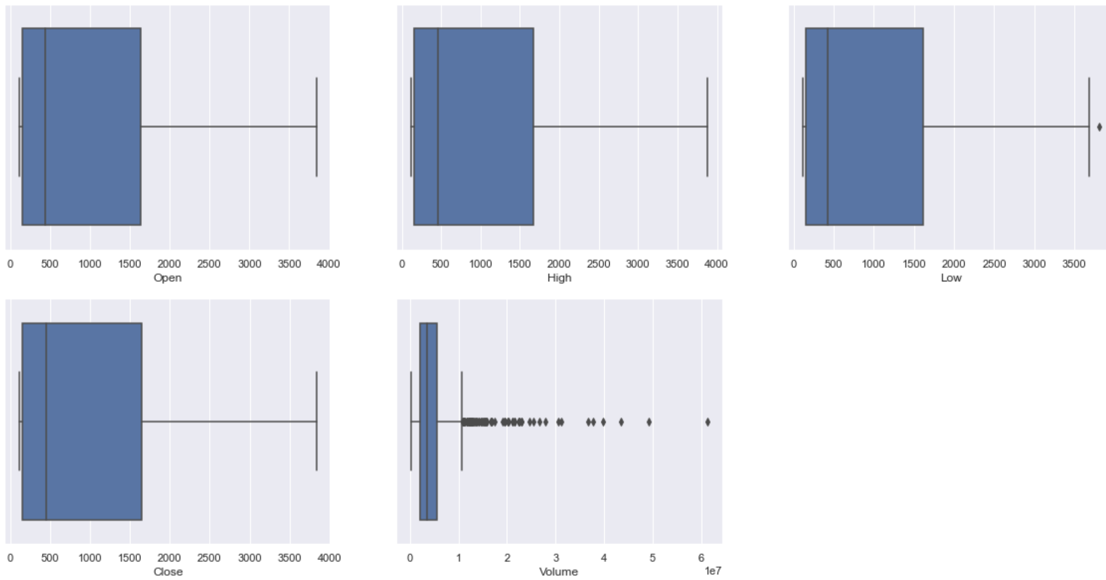
[44]:

```
features = ['Open', 'High', 'Low', 'Close', 'Volume']
plt.subplots(figsize=(20,10))
for i, col in enumerate(features):
  plt.subplot(2,3,i+1)
  sb.distplot(adanient[col])
plt.show()
```



- In the distribution plot of OHLC data, we can see two peaks which means the data has varied significantly in two regions. And the Volume data is left-skewed.

[45]:
```python
plt.subplots(figsize=(20,10))
for i, col in enumerate(features):
  plt.subplot(2,3,i+1)
  sb.boxplot(adanient[col])
plt.show()
```



- From the above boxplots, we can conclude that only volume data contains outliers in it but the data in the rest of the columns are free from any outlier.

1.4 Feature Engineering

[46]:
```python
adanient=adanient.reset_index()
```

[47]:
```python
adanient['year'] = adanient['Date'].dt.year
adanient['month'] = adanient['Date'].dt.month
adanient['day'] = adanient['Date'].dt.day
adanient.head()
```

[47]:
```
        Date        Open        High         Low       Close   Adj Close  \
0 2019-01-01  160.899994  162.350006  155.449997  157.250000  155.465088
1 2019-01-02  157.000000  157.850006  152.500000  154.850006  153.092361
2 2019-01-03  154.899994  156.100006  150.300003  152.500000  150.769012
3 2019-01-04  152.100006  154.000000  150.000000  152.550003  150.818451
4 2019-01-07  152.899994  154.449997  150.250000  151.250000  149.533203

    Volume  Open:30 days rolling  year  month  day
0  4726656                   NaN  2019      1    1
1  2735262                   NaN  2019      1    2
```

```
2   2758876                  NaN  2019      1    3
3   2777308                  NaN  2019      1    4
4   2714218                  NaN  2019      1    7
```

[48]:
```python
# set index using column
adanient = adanient.set_index('Date')
```

[49]:
```python
adanient['is_quarter_end'] = np.where(adanient['month']%3==0,1,0)
adanient.head()
```

[49]:
```
                  Open        High         Low       Close   Adj Close  \
Date
2019-01-01  160.899994  162.350006  155.449997  157.250000  155.465088
2019-01-02  157.000000  157.850006  152.500000  154.850006  153.092361
2019-01-03  154.899994  156.100006  150.300003  152.500000  150.769012
2019-01-04  152.100006  154.000000  150.000000  152.550003  150.818451
2019-01-07  152.899994  154.449997  150.250000  151.250000  149.533203

             Volume  Open:30 days rolling  year  month  day  is_quarter_end
Date
2019-01-01  4726656                   NaN  2019      1    1               0
2019-01-02  2735262                   NaN  2019      1    2               0
2019-01-03  2758876                   NaN  2019      1    3               0
2019-01-04  2777308                   NaN  2019      1    4               0
2019-01-07  2714218                   NaN  2019      1    7               0
```

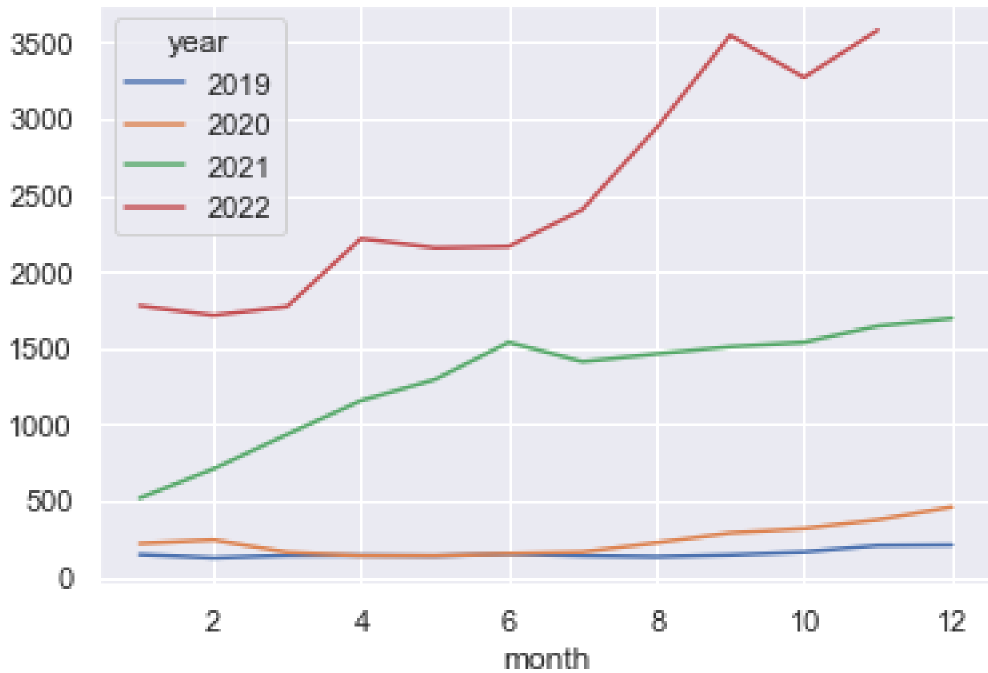
[50]:
```python
adanientPivot = pd.pivot_table(adanient, values = "Close", columns = "year",␣
 ↪index = "month")
```

[51]:
```python
adanientPivot.head()
```

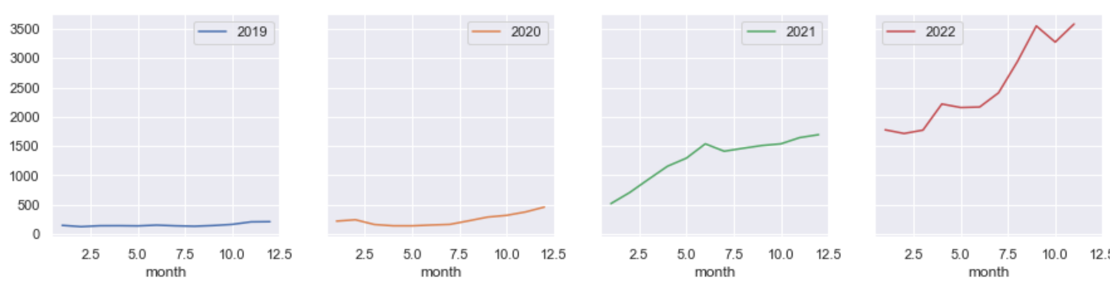
[51]:
```
year         2019        2020         2021         2022
month
1      147.121739  218.793480   517.032498  1776.404993
2      124.339474  242.610524   707.327505  1713.949988
3      140.208334  161.490476   933.876194  1771.292864
4      141.044736  139.463888  1155.536840  2217.150024
5      137.509090  138.813157  1293.480005  2156.814261
```

[52]:
```python
adanientPivot.plot()
```

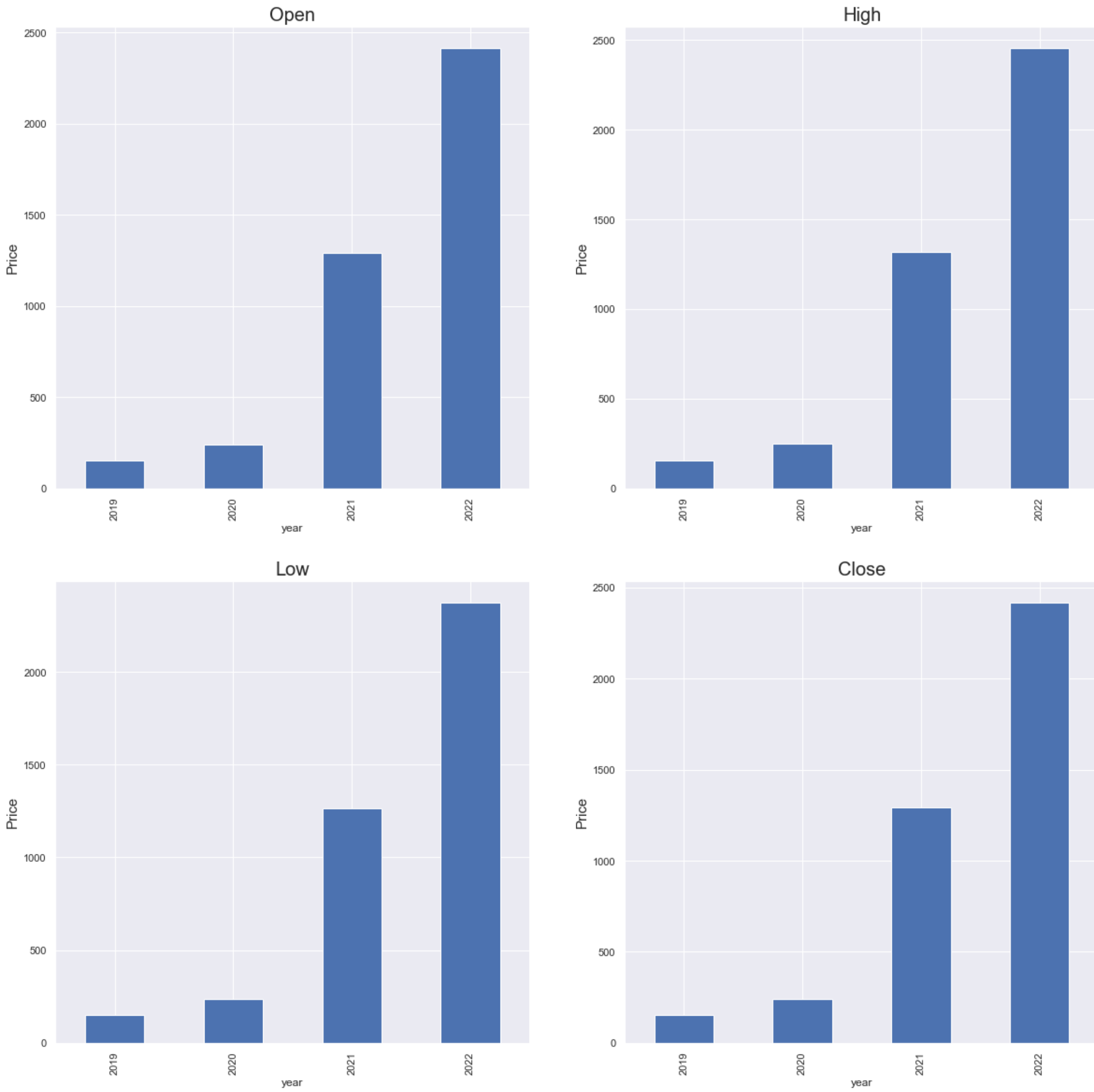
[52]:
```
<AxesSubplot:xlabel='month'>
```



[53]:
```
adanientPivot.plot(subplots = True, figsize=(15, 15), layout=(4,4), sharey=True)
plt.show()
```



[54]:
```
data_grouped = adanient.groupby('year').mean()
plt.subplots(figsize=(20,20))

for i, col in enumerate(['Open', 'High', 'Low', 'Close']):
  plt.subplot(2,2,i+1)
  plt.ylabel('Price', fontsize=15)
  plt.title(col, fontsize=20)
  data_grouped[col].plot.bar()
plt.show()
```



- From the above bar graph, we can conclude that the stock prices have 15 times from the year 2019 to that in 2022.

[55]:
```
adanient.groupby('is_quarter_end').mean()
```

[55]:
```
                       Open         High          Low        Close  \
is_quarter_end
0                941.272633   959.315850   924.765064   943.065141
1               1020.531170  1040.248731  1000.349369  1021.284970

                  Adj Close        Volume  Open:30 days rolling         year  \
is_quarter_end
0                942.172049  4.778843e+06            935.303652  2020.443218
```

```
1                 1020.372904  5.139329e+06            957.697521  2020.443038

                   month        day
is_quarter_end
0               5.862776  15.733438
1               7.281646  15.762658
```

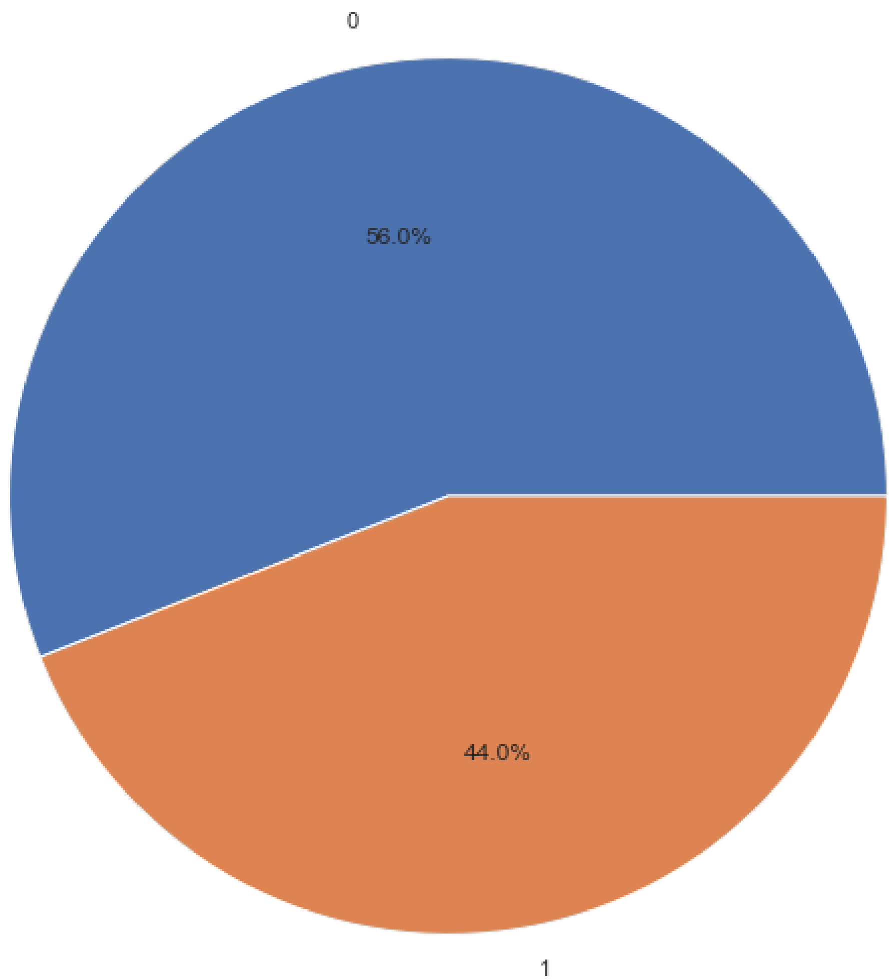
Here are some of the important observations of the above-grouped data:

- Prices are higher in the months which are quarter end as compared to that of the non-quarter end months.
- The volume of trades is lower in the months which are quarter end.

[56]:
```
adanient['open-close']  = adanient['Open'] - adanient['Close']
adanient['low-high']  = adanient['Low'] - adanient['High']
adanient['target'] = np.where(adanient['Close'].shift(-1) > adanient['Close'],␣
↪1, 0)
```

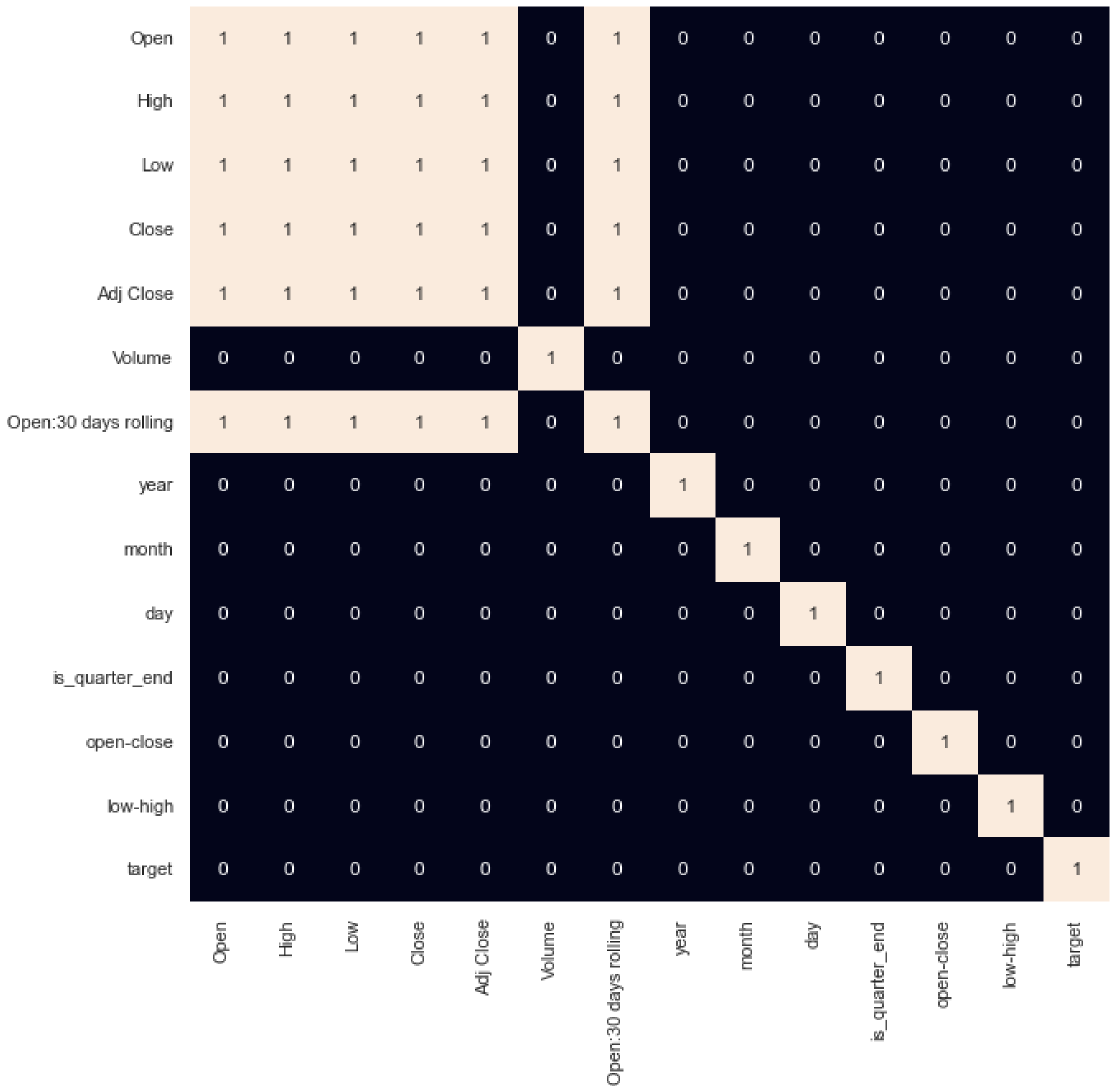
- Above we have added some more columns which will help in the training of our model. We have added the target feature which is a signal whether to buy or not we will train our model to predict this only. But before proceeding let's check whether the target is balanced or not using a pie chart.

[57]:
```
plt.figure(figsize=(10, 10))
plt.pie(adanient['target'].value_counts().values,
        labels=[0, 1], autopct='%1.1f%%')
plt.show()
```



- When we add features to our dataset we have to ensure that there are no highly correlated features as they do not help in the learning process of the algorithm.

[58]:
```
plt.figure(figsize=(10, 10))

# As our concern is with the highly
# correlated features only so, we will visualize
# our heatmap as per that criteria only.
sb.heatmap(adanient.corr() > 0.9, annot=True, cbar=False)
plt.show()
```



- From the above heatmap, we can say that there is a high correlation between OHLC that is pretty obvious and the added features are not highly correlated with each other or previously provided features which means that we are good to go and build our model.

1.5 Data Splitting and Normalization

[59]:
```
features = adanient[['open-close', 'low-high', 'is_quarter_end']]
target = adanient['target']

scaler = StandardScaler()
features = scaler.fit_transform(features)

X_train, X_valid, Y_train, Y_valid = train_test_split(
    features, target, test_size=0.1, random_state=2022)
```

```python
print(X_train.shape, X_valid.shape)
```

```
(855, 3) (95, 3)
```

- After selecting the features to train the model on we should normalize the data because normalized data leads to stable and fast training of the model. After that whole data has been split into two parts with a 90/10 ratio so, that we can evaluate the performance of our model on unseen data.

1.6 Model Development and Evaluation

- Now is the time to train some state-of-the-art machine learning models(Logistic Regression, Support Vector Machine, XGBClassifier), and then based on their performance on the training and validation data we will choose which ML model is serving the purpose at hand better.

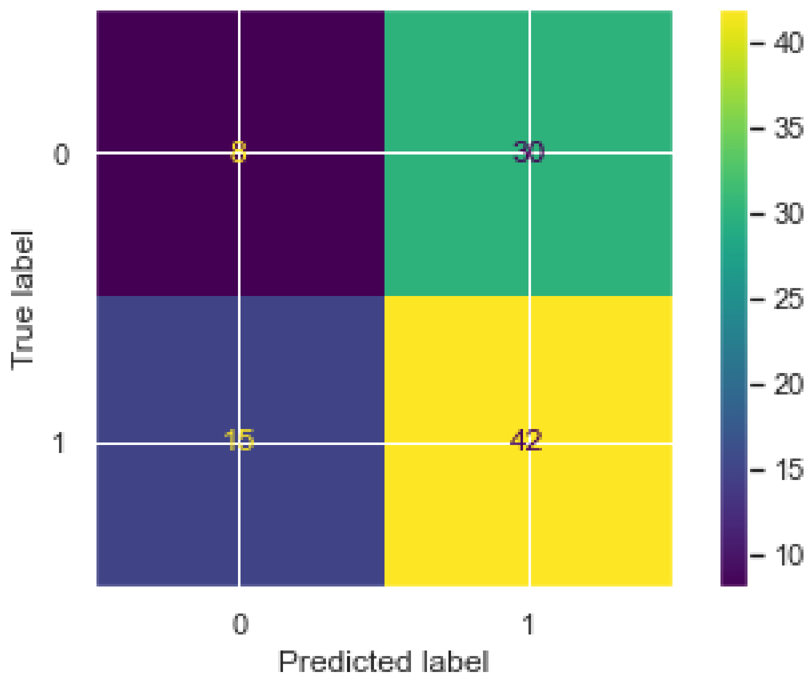
[60]:
```python
models = [LogisticRegression(), SVC(
  kernel='poly', probability=True), XGBClassifier()]

for i in range(3):
  models[i].fit(X_train, Y_train)

  print(f'{models[i]} : ')
  print('Training Accuracy : ', metrics.roc_auc_score(Y_train, models[i].
 ↪predict_proba(X_train)[:,1]))
  print('Validation Accuracy : ', metrics.roc_auc_score(Y_valid, models[i].
 ↪predict_proba(X_valid)[:,1]))
  print()
```

```
LogisticRegression() :
Training Accuracy :  0.5689750692520776
Validation Accuracy :  0.4316712834718375

SVC(kernel='poly', probability=True) :
Training Accuracy :  0.5809085872576177
Validation Accuracy :  0.44182825484764543

XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_bin=256, max_cat_threshold=64, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=0,
…) :
Training Accuracy :  0.9893351800554017
Validation Accuracy :  0.4764542936288088
```

- Among the three models, we have trained XGBClassifier has the highest performance but it is pruned to overfitting as the difference between the training and the validation accuracy is too high. But in the case of the Logistic Regression, this is not the case.
- Now let's plot a confusion matrix for the validation data.

[61]:
```
plt.figure(figsize=(20, 20))
metrics.plot_confusion_matrix(models[0], X_valid, Y_valid)
plt.show()
```

```
<Figure size 1440x1440 with 0 Axes>
```



1.7 Model Linear Regression model

[62]:
```
adanient=adanient.reset_index()
# Setting the layout for our plot
layout = go.Layout(
    title='Stock Prices of Adani Enterprises',
    xaxis=dict(
        title='Date',
        titlefont=dict(
            family='Courier New, monospace',
            size=18,
            color='#7f7f7f'
```

```
            )
        ),
        yaxis=dict(
            title='Price',
            titlefont=dict(
                family='Courier New, monospace',
                size=18,
                color='#7f7f7f'
            )
        )
)

adanient_data = [{'x':adanient['Date'], 'y':adanient['Close']}]
plot = go.Figure(data=adanient_data, layout=layout)
```

[63]:
```
#plot(plot) #plotting offline
iplot(plot)
```

[64]:
```
# Building the regression model
from sklearn.model_selection import train_test_split

#For preprocessing
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression


import chart_studio.plotly as py
import plotly.graph_objs as go
from plotly.offline import plot

#for offline plotting
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)

#For model evaluation
from sklearn.metrics import mean_squared_error as mse
from sklearn.metrics import r2_score
```

[65]:
```
#Split the data into train and test sets
X = np.array(adanient.index).reshape(-1,1)
Y = adanient['Close']
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3,␣
 ↪random_state=101)
```

[66]:
```
# Feature scaling
scaler = StandardScaler().fit(X_train)
```

```
[ ]:
```

```
[67]: #Creating a linear model
      lm = LinearRegression()
      lm.fit(X_train, Y_train)
```

```
[67]: LinearRegression()
```

```
[68]: #Plot actual and predicted values for train dataset
      trace0 = go.Scatter(x = X_train.T[0],y = Y_train,mode = 'markers',name =␣
       ↪'Actual')
      trace1 = go.Scatter(x = X_train.T[0],y = lm.predict(X_train).T,mode =␣
       ↪'lines',name = 'Predicted')
      adanient_data = [trace0,trace1]
      layout.xaxis.title.text = 'Day'
      plot2 = go.Figure(data=adanient_data, layout=layout)
```

```
[69]: iplot(plot2)
```

```
[70]: #Calculate scores for model evaluation
      scores = f'''
      {'Metric'.ljust(10)}{'Train'.center(20)}{'Test'.center(20)}
      {'r2_score'.ljust(10)}{r2_score(Y_train, lm.
       ↪predict(X_train))}\t{r2_score(Y_test, lm.predict(X_test))}
      {'MSE'.ljust(10)}{mse(Y_train, lm.predict(X_train))}\t{mse(Y_test, lm.
       ↪predict(X_test))}
      '''
      print(scores)
```

```
Metric            Train                 Test
r2_score  0.8217821409507651    0.8362676928379684
MSE       160795.17281890797    158270.4011447389
```

1.8 Conclusion:

- We can observe that the accuracy achieved by the state-of-the-art ML model is no better than simply guessing with a probability of 50%. Possible reasons for this may be the lack of data or using a very simple model to perform such a complex task as Stock Market prediction.

```
[ ]:
```