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STOCK PRICE PREDICTION

```
from google.colab import drive
drive.mount('/content/Drive')
```

```
Drive already mounted at /content/Drive; to attempt to forcibly remount, call drive.mount("/content/Drive", force_remount=True).
```

```
#importing the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
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
```

```
data=pd.read_csv('/content/Drive/MyDrive/Colab Notebooks/Stock_Price_data_set.csv')
```

```
data.shape
```

```
(1009, 7)
```

```
data.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2018-02-05	262.000000	267.899994	250.029999	254.259995	254.259995	11896100
1	2018-02-06	247.699997	266.700012	245.000000	265.720001	265.720001	12595800
2	2018-02-07	266.579987	272.450012	264.329987	264.559998	264.559998	8981500
3	2018-02-08	267.079987	267.619995	250.000000	250.100006	250.100006	9306700
4	2018-02-09	253.850006	255.800003	236.110001	249.470001	249.470001	16906900

```
data.tail()
```

	Date	Open	High	Low	Close	Adj Close	Volume
1004	2022-01-31	401.970001	427.700012	398.200012	427.140015	427.140015	20047500
1005	2022-02-01	432.959991	458.480011	425.540009	457.130005	457.130005	22542300
1006	2022-02-02	448.250000	451.980011	426.480011	429.480011	429.480011	14346000
1007	2022-02-03	421.440002	429.260010	404.279999	405.600006	405.600006	9905200
1008	2022-02-04	407.309998	412.769989	396.640015	410.170013	410.170013	7782400

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1009 entries, 0 to 1008
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Date       1009 non-null   object 
 1   Open       1009 non-null   float64
 2   High       1009 non-null   float64
 3   Low        1009 non-null   float64
 4   Close      1009 non-null   float64
 5   Adj Close  1009 non-null   float64
 6   Volume     1009 non-null   int64  
dtypes: float64(5), int64(1), object(1)
memory usage: 55.3+ KB
```

```
data.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	1009.000000	1009.000000	1009.000000	1009.000000	1009.000000	1.009000e+03
mean	419.059673	425.320703	412.374044	419.000733	419.000733	7.570685e+06
std	108.537532	109.262960	107.555867	108.289999	108.289999	5.465535e+06
min	233.919998	250.649994	231.229996	233.880005	233.880005	1.144000e+06
25%	331.489990	336.299988	326.000000	331.619995	331.619995	4.091900e+06
50%	377.769989	383.010010	370.880005	378.670013	378.670013	5.934500e+06
75%	509.130005	515.630005	502.529999	509.079987	509.079987	9.322400e+06
max	692.349976	700.989990	686.090027	691.690002	691.690002	5.890430e+07

```
data['Date']
```

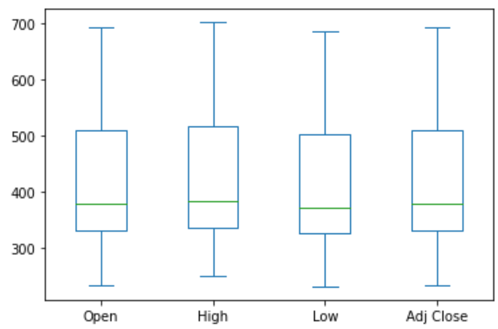
```
0       2018-02-05
1       2018-02-06
2       2018-02-07
3       2018-02-08
4       2018-02-09
           ...
1004    2022-01-31
1005    2022-02-01
1006    2022-02-02
1007    2022-02-03
1008    2022-02-04
Name: Date, Length: 1009, dtype: object
```

```
data.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	1009.000000	1009.000000	1009.000000	1009.000000	1009.000000	1.009000e+03
mean	419.059673	425.320703	412.374044	419.000733	419.000733	7.570685e+06
std	108.537532	109.262960	107.555867	108.289999	108.289999	5.465535e+06
min	233.919998	250.649994	231.229996	233.880005	233.880005	1.144000e+06
25%	331.489990	336.299988	326.000000	331.619995	331.619995	4.091900e+06
50%	377.769989	383.010010	370.880005	378.670013	378.670013	5.934500e+06
75%	509.130005	515.630005	502.529999	509.079987	509.079987	9.322400e+06
max	692.349976	700.989990	686.090027	691.690002	691.690002	5.890430e+07

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f614afcd130>
```




```
plt.figure(figsize=(15,5))
plt.plot(data['Close'])
plt.title('Close Price.',fontsize=18)
plt.ylabel('Price')
plt.show()
```


```
1 data.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2018-02-05	262.000000	267.899994	250.029999	254.259995	254.259995	11896100
1	2018-02-06	247.699997	266.700012	245.000000	265.720001	265.720001	12595800
2	2018-02-07	266.579987	272.450012	264.329987	264.559998	264.559998	8981500
3	2018-02-08	267.079987	267.619995	250.000000	250.100006	250.100006	9306700
4	2018-02-09	253.850006	255.800003	236.110001	249.470001	249.470001	16906900

If we observe carefully we can see that the data in the ‘Close’ column and that available in the ‘Adj Close’ column is the same let’s check whether this is the case with each row or not.

```
1 data[data['Close']==data['Adj Close']].shape
```

```
(1009, 7)
```

From here we can conclude that all the rows of columns ‘Close’ and ‘Adj Close’ have the same data. So, having redundant data in the dataset is not going to help so, we’ll drop this column before further analysis.

```
1 data.drop(['Adj Close'],axis=1)
```

	Date	Open	High	Low	Close	Volume
0	2018-02-05	262.000000	267.899994	250.029999	254.259995	11896100
1	2018-02-06	247.699997	266.700012	245.000000	265.720001	12595800
2	2018-02-07	266.579987	272.450012	264.329987	264.559998	8981500
3	2018-02-08	267.079987	267.619995	250.000000	250.100006	9306700
4	2018-02-09	253.850006	255.800003	236.110001	249.470001	16906900
...	...	...	...	...	...	...
1004	2022-01-31	401.970001	427.700012	398.200012	427.140015	20047500
1005	2022-02-01	432.959991	458.480011	425.540009	457.130005	22542300
1006	2022-02-02	448.250000	451.980011	426.480011	429.480011	14346000
1007	2022-02-03	421.440002	429.260010	404.279999	405.600006	9905200
1008	2022-02-04	407.309998	412.769989	396.640015	410.170013	7782400

1009 rows × 6 columns

Now let’s draw the distribution plot for the continuous features given in the dataset.

Before moving further let’s check for the null values if any are present in the data frame.

```
1 data.isnull().sum()
```

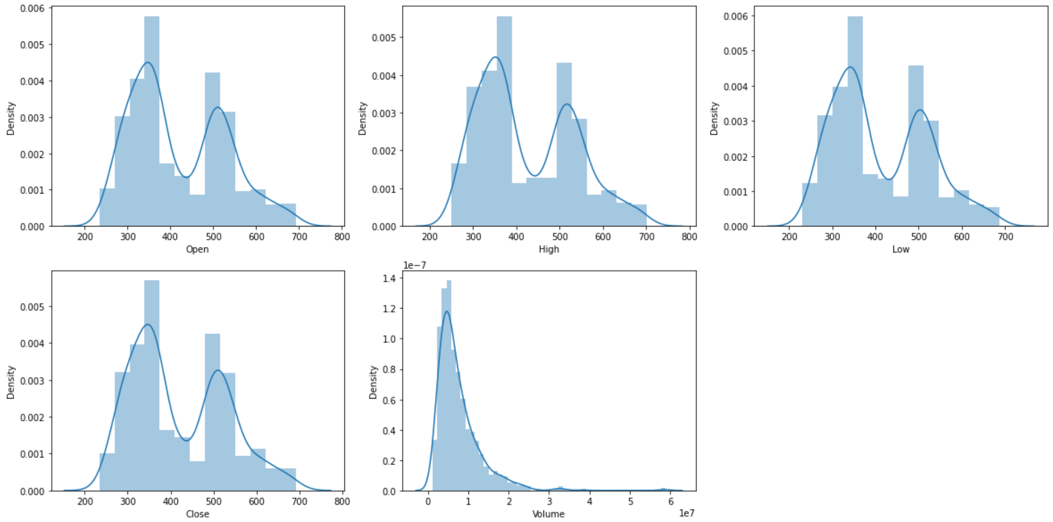
```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

This implies there is no null value in the data set provided

```
#plotting some graphs
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(data[col])
plt.show()
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a de
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.8/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a de
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.8/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a de
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.8/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a de
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.8/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a de
  warnings.warn(msg, FutureWarning)
```

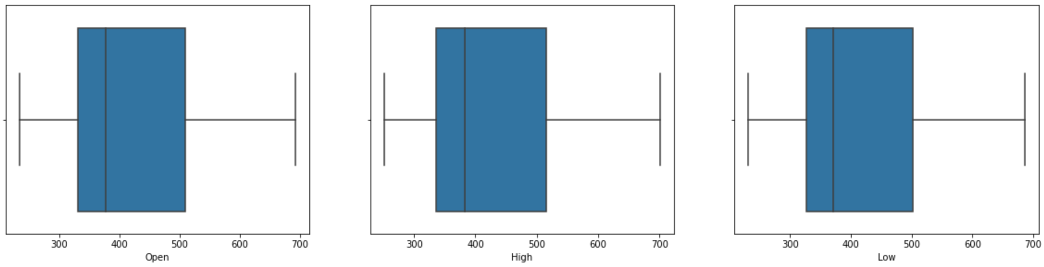


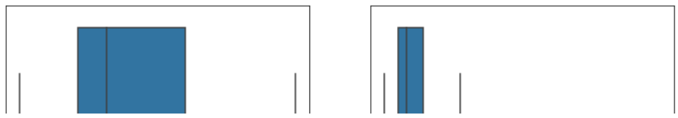
we can see two peaks which means the data has varied significantly in two regions. And the Volume data is left-skewed.

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

plt.show()
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following var
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following var
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following var
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following var
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following var
  warnings.warn(
```





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.

```
splitted = data['Date'].str.split('-', expand=True)
data['day'] = splitted[2].astype('int')
data['month'] = splitted[1].astype('int')
data['year'] = splitted[0].astype('int')



data.head()

```

	Date	Open	High	Low	Close	Adj Close	Volume	day	month	year
0	2018-02-05	262.000000	267.899994	250.029999	254.259995	254.259995	11896100	5	2	2018
1	2018-02-06	247.699997	266.700012	245.000000	265.720001	265.720001	12595800	6	2	2018
2	2018-02-07	266.579987	272.450012	264.329987	264.559998	264.559998	8981500	7	2	2018
3	2018-02-08	267.079987	267.619995	250.000000	250.100006	250.100006	9306700	8	2	2018
4	2018-02-09	253.850006	255.800003	236.110001	249.470001	249.470001	16906900	9	2	2018

Now we have three more columns namely 'day', 'month' and 'year' all these three have been derived from the 'Date' column which was initially provided in the data.

```
data['is_quarter_end'] = np.where(data['month']%3==0,1,0)
data.head()

```

	Date	Open	High	Low	Close	Adj Close	Volume	day	month	year	is_quart
0	2018-02-05	262.000000	267.899994	250.029999	254.259995	254.259995	11896100	5	2	2018	
1	2018-02-06	247.699997	266.700012	245.000000	265.720001	265.720001	12595800	6	2	2018	
2	2018-02-07	266.579987	272.450012	264.329987	264.559998	264.559998	8981500	7	2	2018	
	2018-										

A quarter is defined as a group of three months. Every company prepares its quarterly results and publishes them publicly so, that people can analyze the company's performance. These quarterly results affect the stock prices heavily which is why we have added this feature because this can be a helpful feature for the learning model.

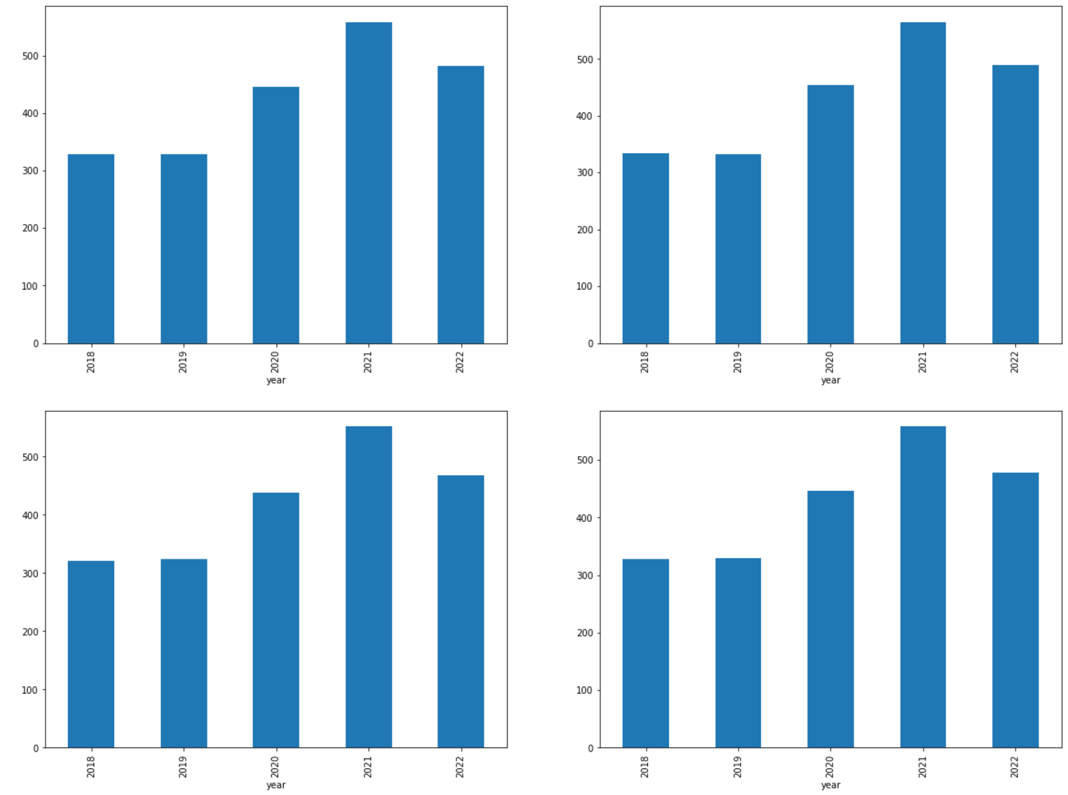
```
data_grouped = data.groupby('year').mean()
plt.subplots(figsize=(20,15))

for i, col in enumerate(['Open', 'High', 'Low', 'Close']):
```

```

  plt.subplot(2,2,i+1)
  data_grouped[col].plot.bar()
plt.show()

```




```
data.groupby('is_quarter_end').mean()

```

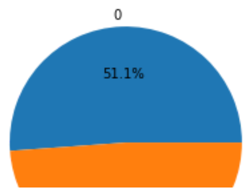
	Open	High	Low	Close	Adj Close	Volume	day	mo
is_quarter_end								
0	418.681368	424.889821	412.112068	418.699791	418.699791	7.951664e+06	15.715774	6.087
1	419.814037	426.179910	412.896440	419.600831	419.600831	6.810988e+06	15.721068	7.442

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

```

```
plt.pie(data['target'].value_counts().values,
        labels=[0, 1], autopct='%1.1f%%')
plt.show()

```

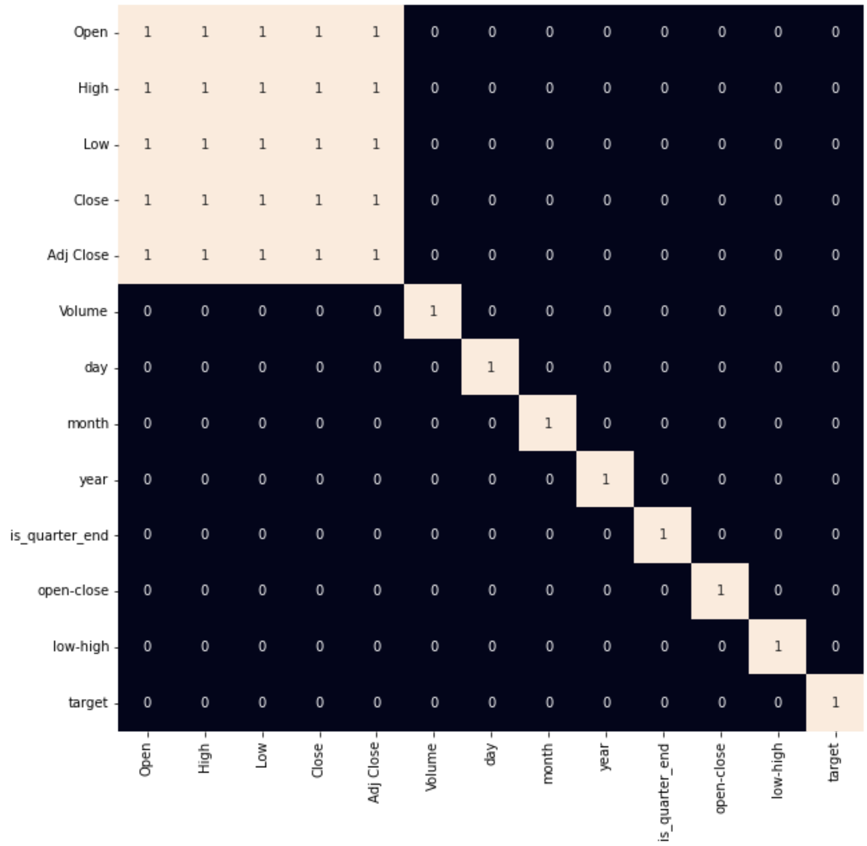


When we add features to our dataset we have to ensure that there are no highly correlated features as they do not help in the learning process of the algorithm.

```
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(data.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.

```
#Data Splitting and Normalization
features = data[['open-close', 'low-high', 'is_quarter_end']]
target = data['target']

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

X_train, X_test, Y_train, Y_test = train_test_split(
    features, target, test_size=0.1, random_state=2022)
print(X_train.shape, X_test.shape)

```

```
(908, 3) (101, 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.

```
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('Testing Accuracy : ', metrics.roc_auc_score(Y_test, models[i].predict_proba(X_test)[:,1]))
  print()

```

```
LogisticRegression() :
Training Accuracy :  0.5406138368447911
Testing Accuracy :  0.582598235765838

SVC(kernel='poly', probability=True) :
Training Accuracy :  0.5325945906539331
Testing Accuracy :  0.4947874899759423

XGBClassifier() :
Training Accuracy :  0.7993268693348886
Testing Accuracy :  0.60084202085004
```

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 testing accuracy is high. But in the case of the Logistic Regression, this is not the case.

Now let's plot a confusion matrix for the testing data.

```
metrics.plot_confusion_matrix(models[0], X_test, Y_test)
plt.show()

```

```
/usr/local/lib/python3.8/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning
  warnings.warn(msg, category=FutureWarning)
```