stock-price-prediction-python

February 2, 2024

1 Stock Price Prediction using Machine Learning in Python

I will build a model that will predict a signal that indicates whether buying a particular stock will be helpful or not by using ML.

1.0.1 Import Libraries

[1]:
```
import numpy as np
 import pandas as pd
 import matplotlib.pyplot as plt
 import seaborn as sns

 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

 import warnings
 warnings.filterwarnings('ignore')
```

1.0.2 Import dataset

dataset: https://www.kaggle.com/datasets/timoboz/tesla-stock-data-from-2010-to-2020

[2]:
```
# Loading the data set from system drive
from google.colab import files
uploaded = files.upload()
# Choose the data to uploafd from the file manager
```

```
<IPython.core.display.HTML object>
```

```
Saving TSLA.csv to TSLA.csv
```

[4]:
```
import io
# Now using io i will access the data where it is stored
df = pd.read_csv(io.BytesIO(uploaded['TSLA.csv']),encoding = 'latin-1').
 ↪dropna(axis = 1)
```

```
df.head()
```

[4]:

```
         Date       Open   High        Low      Close  Adj Close    Volume
0  2010-06-29  19.000000  25.00  17.540001  23.889999  23.889999  18766300
1  2010-06-30  25.790001  30.42  23.299999  23.830000  23.830000  17187100
2  2010-07-01  25.000000  25.92  20.270000  21.959999  21.959999   8218800
3  2010-07-02  23.000000  23.10  18.709999  19.200001  19.200001   5139800
4  2010-07-06  20.000000  20.00  15.830000  16.110001  16.110001   6866900
```

I will use OHLC('Open', 'High', 'Low', 'Close') data from 1st January 2010 to 31st December 2020 which is for 8 years for the Tesla stocks.

[5]:

```
# Shape of the Data
df.shape
```

[5]: (2416, 7)

[6]:

```
# Now we get the summary of the data
df.describe()
```

[6]:

```
              Open         High          Low        Close    Adj Close  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean    186.271147   189.578224   182.916639   186.403651   186.403651
std     118.740163   120.892329   116.857591   119.136020   119.136020
min      16.139999    16.629999    14.980000    15.800000    15.800000
25%      34.342498    34.897501    33.587501    34.400002    34.400002
50%     213.035004   216.745002   208.870002   212.960007   212.960007
75%     266.450012   270.927513   262.102501   266.774994   266.774994
max     673.690002   786.140015   673.520020   780.000000   780.000000

             Volume
count  2.416000e+03
mean   5.572722e+06
std    4.987809e+06
min    1.185000e+05
25%    1.899275e+06
50%    4.578400e+06
75%    7.361150e+06
max    4.706500e+07
```

[7]:

```
# Info of the data set
df.info()
```

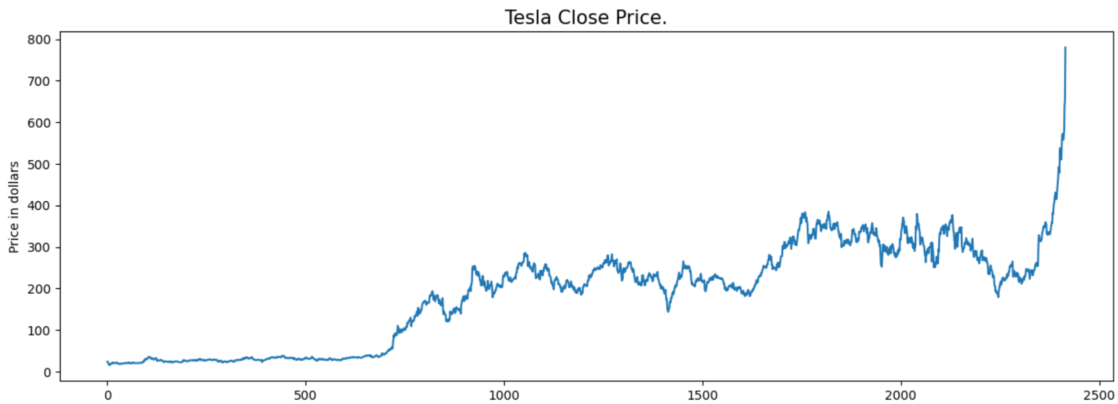
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2416 entries, 0 to 2415
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
```

```
 0   Date       2416 non-null   object
 1   Open       2416 non-null   float64
 2   High       2416 non-null   float64
 3   Low        2416 non-null   float64
 4   Close      2416 non-null   float64
 5   Adj Close  2416 non-null   float64
 6   Volume     2416 non-null   int64
dtypes: float64(5), int64(1), object(1)
memory usage: 132.2+ KB
```

2 Exploratory Data Analysis

While performing the EDA of the Tesla Stock Price data I 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.

[8]:
```
plt.figure(figsize=(15,5))
plt.plot(df['Close'])
plt.title('Tesla Close Price.', fontsize = 15)
plt.ylabel('Price in dollars')
plt.show()
by = 'Joseph Wathome'
```



The prices of tesla stocks are showing an upward trend as depicted by the plot of the closing price of the stocks.

[9]:
```
df.head()
```

[9]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2010-06-29	19.000000	25.00	17.540001	23.889999	23.889999	18766300
1	2010-06-30	25.790001	30.42	23.299999	23.830000	23.830000	17187100
2	2010-07-01	25.000000	25.92	20.270000	21.959999	21.959999	8218800
3	2010-07-02	23.000000	23.10	18.709999	19.200001	19.200001	5139800
4	2010-07-06	20.000000	20.00	15.830000	16.110001	16.110001	6866900

if we observe we can see that 'Close' adn 'Adj Close' are the same lets check if if its true in every row

[10]:
```
df[df['Close'] == df['Adj Close']].shape
```

[10]:
```
(2416, 7)
```

therefore we have Redundant data in the data set, lets drop this column b4 further analysis

[11]:
```
df = df.drop(['Adj Close'], axis =1)
```

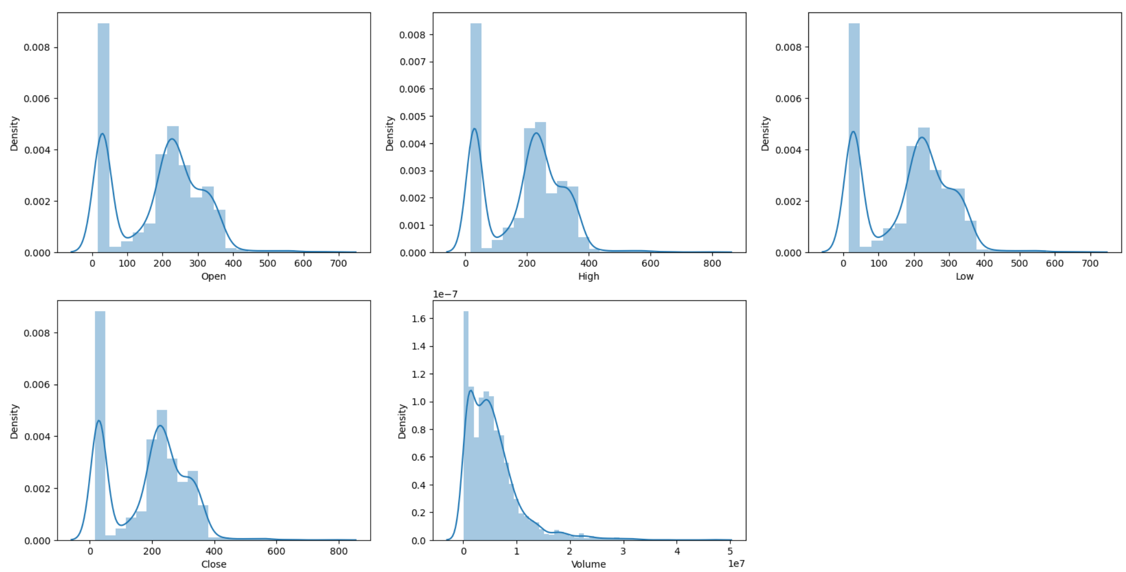
Check for null values

[12]:
```
df.isnull().sum()
```

[12]:
```
Date      0
Open      0
High      0
Low       0
Close     0
Volume    0
dtype: int64
```

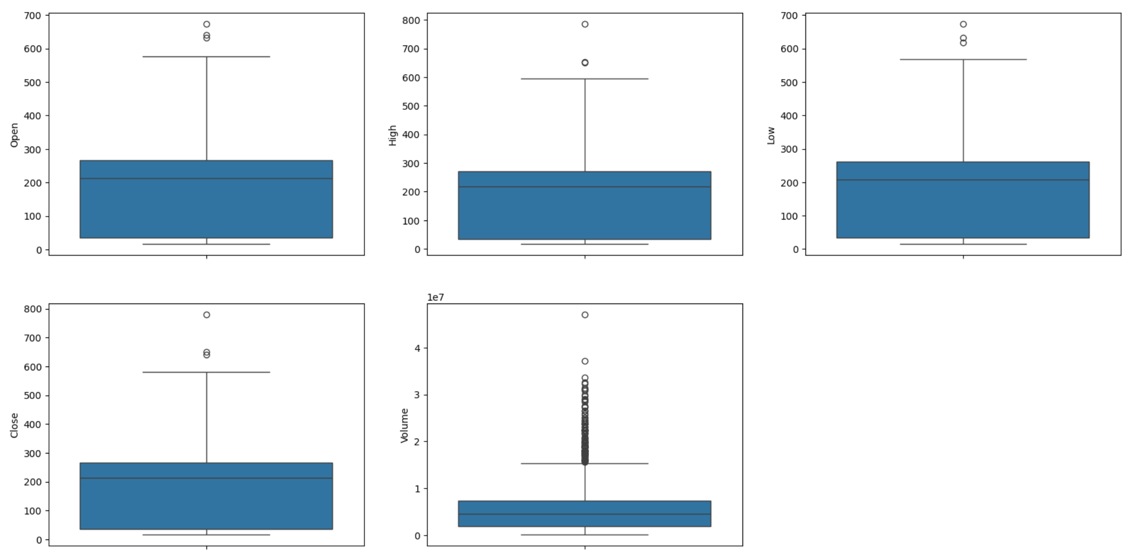
I will plot the distribution plot for the continous features given in the dataset

[13]:
```
features = ['Open', 'High', 'Low', 'Close', 'Volume']

plt.subplots(figsize=(20, 10))

for i, col in enumerate(features):
  plt.subplot(2, 3, i+1)
  sns.distplot(df[col])

plt.show()
```



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

[14]:
```
# Boxplot
plt.subplots(figsize=(20,10))
for i, col in enumerate(features):
  plt.subplot(2,3, i+1)
  sns.boxplot(df[col])

plt.show()
```



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

2.1 Feature Engineering

[15]:
```python
splitted = df['Date'].str.split('-', expand = True)

df['day'] = splitted[2].astype('int')
df['month'] = splitted[1].astype('int')
df['year'] = splitted[0].astype('int')

df.head()
```

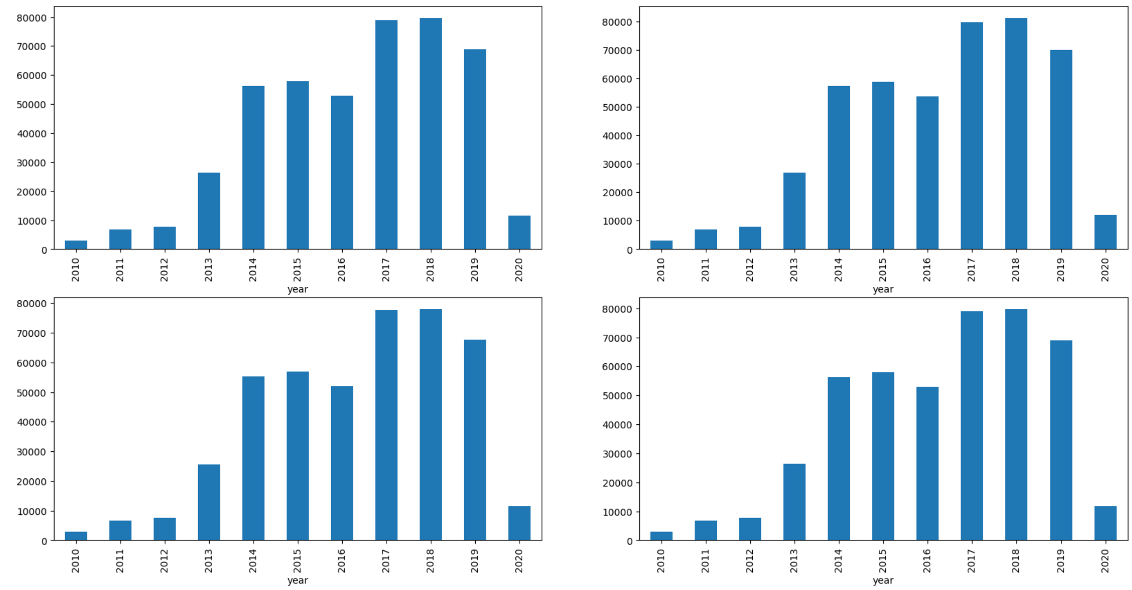
[15]:
```
         Date       Open   High        Low      Close    Volume  day  month  \
0  2010-06-29  19.000000  25.00  17.540001  23.889999  18766300   29      6
1  2010-06-30  25.790001  30.42  23.299999  23.830000  17187100   30      6
2  2010-07-01  25.000000  25.92  20.270000  21.959999   8218800    1      7
3  2010-07-02  23.000000  23.10  18.709999  19.200001   5139800    2      7
4  2010-07-06  20.000000  20.00  15.830000  16.110001   6866900    6      7

   year
0  2010
1  2010
2  2010
3  2010
4  2010
```

[16]:
```python
df['is_quarter_end'] = np.where(df['month']%3==0,1,0)
df.head()
```

[16]:
```
         Date       Open   High        Low      Close    Volume  day  month  \
0  2010-06-29  19.000000  25.00  17.540001  23.889999  18766300   29      6
1  2010-06-30  25.790001  30.42  23.299999  23.830000  17187100   30      6
2  2010-07-01  25.000000  25.92  20.270000  21.959999   8218800    1      7
3  2010-07-02  23.000000  23.10  18.709999  19.200001   5139800    2      7
4  2010-07-06  20.000000  20.00  15.830000  16.110001   6866900    6      7

   year  is_quarter_end
0  2010               1
1  2010               1
2  2010               0
3  2010               0
4  2010               0
```

A quarter is defined as a group of 3 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 I have added this feature because this can be a helpful feature for the learning model.

```
[17]: # Lets view the performance of every year first

data_grouped = df.groupby('year').sum()
plt.subplots(figsize=(20,10))

for i, col in enumerate(['Open', 'High', 'Low', 'Close']):
  plt.subplot(2,2,i+1)
  data_grouped[col].plot.bar()
plt.show()
```



From the above bar graph, we can conclude that the stock prices have doubled from the year 2013 to that in 2014.

```
[18]: df.groupby('is_quarter_end').mean()
```

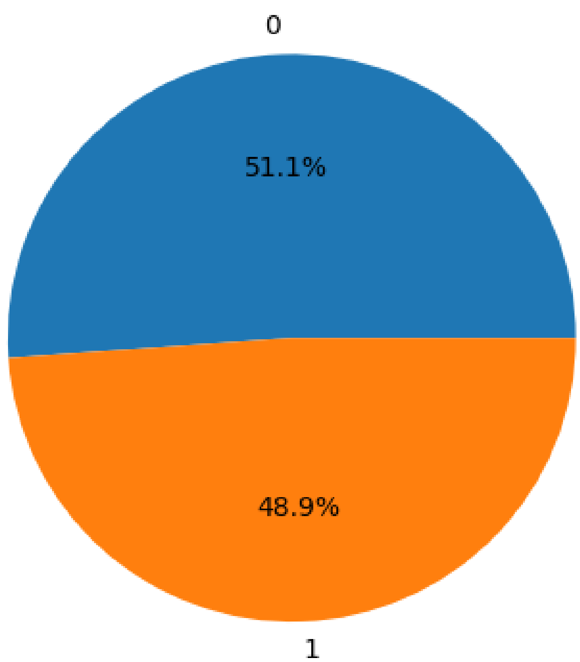
```
[18]:                     Open        High         Low       Close        Volume  \
is_quarter_end
0               185.875081  189.254226  182.449499  186.085081  5.767062e+06
1               187.071200  190.232700  183.860262  187.047163  5.180154e+06

                      day     month         year
is_quarter_end
0               15.710396  6.173886  2014.816213
1               15.825000  7.597500  2014.697500
```

- 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.

[19]:
```
df['open-close'] = df['Open'] - df['Close']
df['low-high'] = df['Low'] - df['High']
df['target'] = np.where(df['Close'].shift(-1) > df['Close'],1,0)
```

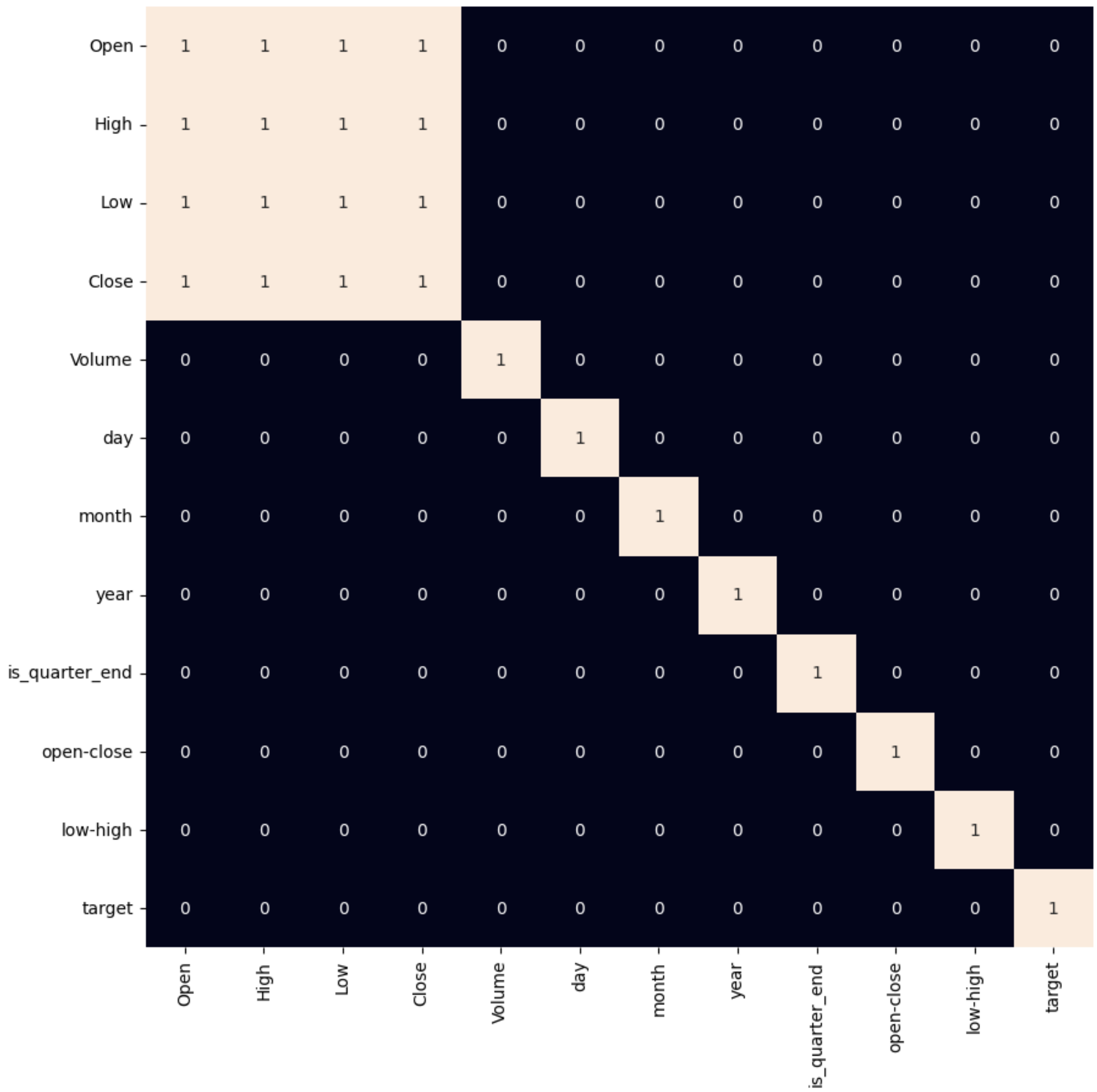
Above I have added some more columns which will help in the training of our model. I have added the target feature which is a signal whether to buy or not I will train The model to predict this only. But before proceeding I will check whether the target is balanced or not using a pie chart.

[20]:
```
plt.pie(df['target'].value_counts().values, labels =[0,1], autopct = '%1.1f%%')
plt.show()
```



when adding Features to any dataset, we should be very careful they are not highly correlated because they won't help in the learning process of the alogarithm

[21]:
```
plt.figure(figsize=(10,10))
# because my concern is with only the with the highly correlated  features,
# i will only visualize that using a heatmap
sns.heatmap(df.corr()> 0.9, annot = True, cbar =False)
plt.show()
```



From the above heatmap, I 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 I am good to go and build our model.

2.1.1 Data Splitting and Normalization

[22]:
```
features = df[['open-close', 'low-high', 'is_quarter_end']]
target   = df['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)
print(X_train.shape, X_valid.shape)
```

```
(2174, 3) (242, 3)
```

2.2 Model Development and Evaluation

I will Train models(Logistic Regression, Support Vector Machine, XGBClassifier), and then based on their performance on the training and validation data I will choose which ML model is serving the purpose at hand better.

for the evaluation metrics i will use the ROC-AUC Curve - This is because instead of predicting the hard probability that is 0 or 1 I would like it to predict soft probabilities that are continuous values between 0 to 1. And with soft probabilities, the ROC-AUC curve is generally used to measure the accuracy of the predictions.

[23]:
```
models = [LogisticRegression(), SVC(kernel = 'poly',
                                    probability = True),␣
↪XGBClassifier(max_depth=3, learning_rate=0.1)]

model_names = ['Logistic Regression', 'SVC', 'XGBClassifier']

min_diff = float('inf')  # Initialize minimum difference as infinity
best_model = None  # Initialize best model as None

for i in range(3):
  models[i].fit(X_train, Y_train)
  training = metrics.roc_auc_score(Y_train, models[i].predict_proba(X_train)[:
↪,1])
  validation = metrics.roc_auc_score(Y_valid, models[i].predict_proba(X_valid)[:
↪,1])
  diff = abs(training - validation)  # Calculate absolute difference

  print(f'{model_names[i]} : ')
  print('Training Accuracy : ', training)
  print('Validation Accuracy : ', validation)
  print('Difference in accuracy of the training and validation : ', diff)
  print()

  # Update minimum difference and best model
  if diff < min_diff:
    min_diff = diff
    best_model = model_names[i]

print(f'The best performing model is {best_model} with a difference of␣
↪{min_diff} between training and validation accuracy.')
```

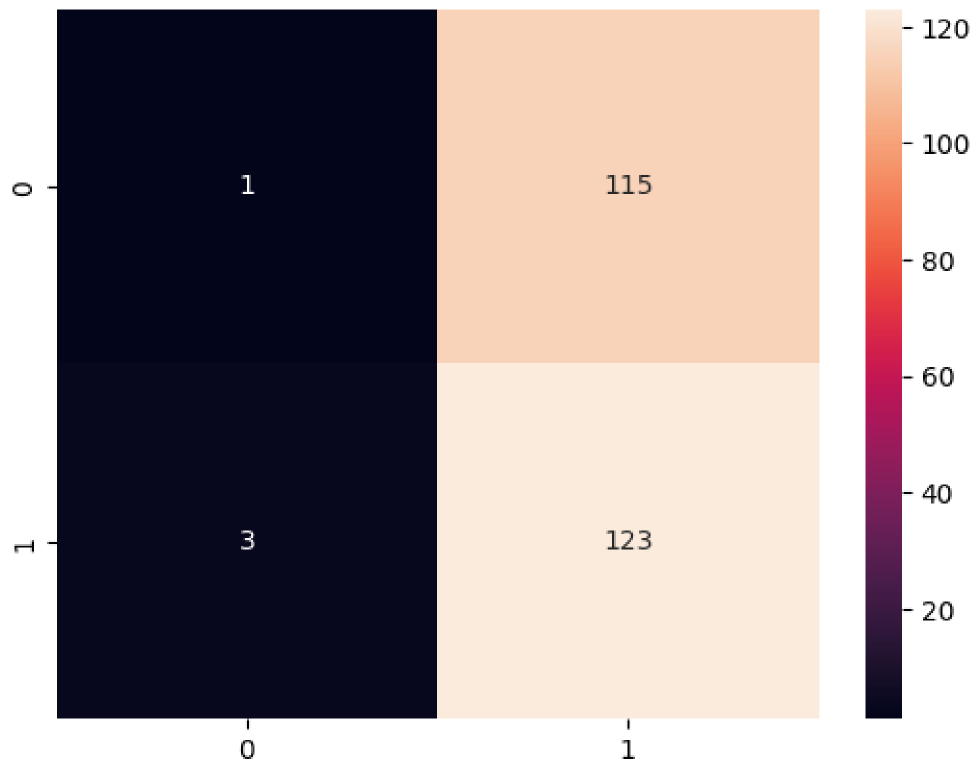
```
Logistic Regression :
Training Accuracy :  0.5228802330060918
Validation Accuracy :  0.4923371647509579
Difference in accuracy of the training and validation :  0.030543068255133865

SVC :
Training Accuracy :  0.5294572363547078
Validation Accuracy :  0.46257525998905313
Difference in accuracy of the training and validation :  0.06688197636565463

XGBClassifier :
Training Accuracy :  0.7113789439371425
Validation Accuracy :  0.5041050903119868
Difference in accuracy of the training and validation :  0.2072738536251557

The best performing model is Logistic Regression with a difference of
0.030543068255133865 between training and validation accuracy.
```

we find the logistic regression model is the best performing model in the training and testing and testing data.

Confusion Matrix

[25]:
```python
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(Y_valid, models[1].predict(X_valid))
sns.heatmap(cm , annot=True, fmt='d')
cm_df = pd.DataFrame(cm)
print(cm_df)
```

```
   0    1
0  1  115
1  3  123
```



From these values, we can calculate various performance metrics:

Accuracy: (TP + TN) / (TP + TN + FP + FN) = (123 + 1) / (123 + 1 + 115 + 3) = 0.51 or 51%. This is the proportion of correct predictions (both positive and negative) out of all predictions.

Precision: TP / (TP + FP) = 123 / (123 + 115) = 0.52 or 52%. This is the proportion of true positive predictions out of all positive predictions.

Recall or Sensitivity: TP / (TP + FN) = 123 / (123 + 3) = 0.98 or 98%. This is the proportion of true positive predictions out of all actual positive instances.

The Training Accuracy is 0.52 (**52%**) and the Validation Accuracy is 0.49 (**49%**). The difference between the training and validation accuracy is about 0.03 (3%), which suggests that the model is not overfitting significantly, as the performance on the training and validation sets is quite similar.

However, the overall accuracy of the model is quite low (around 50%), which suggests that the model's predictions are not very accurate. mainly Due to luck of enough Comprihensive data

[26]:
```
print(by)
```

```
Joseph Wathome
```