Logistic_Regression_Project (1)

December 9, 2024

Project Title

Stock price prediction system

Project Description

The aim of this project is to develop a stock price prediction system for Tesla that generates actionable buy or no-buy signals based on historical stock data. Specifically, the system will predict whether purchasing Tesla stock will be beneficial by analyzing past performance and trends.

Data Source: • The project uses historical stock data from Tesla, which includes key metrics such as the stock's opening, closing, high, and low prices, along with the trading volume.

Goal: • To predict a binary signal indicating whether the stock's closing price on the next trading day will be higher (buy signal) or lower (no-buy signal) compared to the current day's closing price.

Use Case: • The prediction system is designed to assist investors and traders by providing an automated recommendation on whether to buy Tesla stock. This recommendation is based on historical data patterns and trends.

Data Collection and Preparation: • Load the Tesla stock dataset and preprocess the data. This includes handling missing values, removing redundant columns, and preparing the data for analysis.

Feature Engineering: • Create new features that may enhance model performance. This includes calculating price differences (e.g., open-close) and adding time-based indicators such as quarter-end markers.

Exploratory Data Analysis (EDA): • Perform EDA to understand the dataset's structure, identify trends, and analyze correlations between features. This helps in gaining insights and preparing the data for modeling.

Model Building: • Develop machine learning models to classify the buy or no-buy signals. Algorithms such as Logistic Regression and Support Vector Machine (SVM) will be used to make these predictions.

Model Evaluation: • Assess the performance of the models using appropriate metrics (e.g., ROC-AUC) to determine which model provides the most reliable and accurate predictions. The best performing model will be selected based on its ability to generalize to unseen data.

Target Variable (For Supervised Learning)

1. Definition: The target variable is a binary indicator that represents whether it is potentially profitable to buy Tesla stock based on its predicted price movement from one day to the next.
2. How It's Calculated:

- 1 (Buy Signal): The target variable is set to 1 if the closing price of the Tesla stock on the next trading day is expected to be higher than the closing price on the current day. This prediction suggests a potential opportunity to buy the stock because the model forecasts a price increase.
- 0 (Don't Buy Signal): The target variable is set to 0 if the closing price of the Tesla stock on the next trading day is expected to be lower or the same as the closing price on the current day. This prediction suggests that it may not be advantageous to buy the stock because the model does not forecast a price increase.

3. How to Determine the Target Variable:

• To determine whether the target is 1 or 0, the model compares the closing price of today with the predicted closing price of the next trading day. • If Next_Day_Close > Today_Close, then the target is set to 1 (indicating a buy signal). • If Next_Day_Close <= Today_Close, then the target is set to 0 (indicating a no-buy signal). 4.
Use in Decision-Making: • The target variable helps in making stock trading decisions by predicting the direction of the stock price. A '1' (Buy Signal) indicates a potential opportunity to profit by purchasing the stock, while a '0' (Don't Buy Signal) suggests avoiding a purchase due to expected price stagnation or decline.

[169]:
```python
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).
```

Import Libraries

[170]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Machine Learning tools

[171]:
```python
from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
↪TimeSeriesSplit #Hyperparameter tuning (RandomSearchCV)
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (
    classification_report,
    precision_recall_curve,
    roc_curve,
    auc,
    confusion_matrix,
    roc_auc_score,
)
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import TomekLinks
```

```python
from scipy.stats import uniform

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

Load the dataset

[172]:
```python
df = pd.read_csv('/content/drive/My Drive/ML Assignment/TSLA.csv')
```

[173]:
```python
df.head()
```

[173]:
```
         Date       High        Low       Open      Close      Volume  \
0  2019-09-30  48.796001  47.222000  48.599998  48.174000  29399000.0
1  2019-10-01  49.189999  47.826000  48.299999  48.938000  30813000.0
2  2019-10-02  48.930000  47.886002  48.658001  48.625999  28157000.0
3  2019-10-03  46.896000  44.855999  46.372002  46.605999  75422500.0
4  2019-10-04  46.956001  45.613998  46.321999  46.285999  39975000.0

   Adj Close
0  48.174000
1  48.938000
2  48.625999
3  46.605999
4  46.285999
```

[174]:
```python
df.tail()
```

[174]:
```
           Date         High          Low         Open        Close  \
634  2022-04-05  1152.869995  1087.300049  1136.300049  1091.260010
635  2022-04-06  1079.000000  1027.699951  1073.469971  1045.760010
636  2022-04-07  1076.589966  1021.539978  1052.390015  1057.260010
637  2022-04-08  1048.439941  1022.440002  1043.209961  1025.489990
638  2022-04-11  1008.469971   974.640015   980.400024   975.929993

         Volume    Adj Close
634  26691700.0  1091.260010
635  29782800.0  1045.760010
636  26482400.0  1057.260010
637  18293300.0  1025.489990
638  19660500.0   975.929993
```

[175]:
```python
df.shape
```

[175]: (639, 7)

[176]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 639 entries, 0 to 638
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       639 non-null    object
 1   High       639 non-null    float64
 2   Low        639 non-null    float64
 3   Open       639 non-null    float64
 4   Close      639 non-null    float64
 5   Volume     639 non-null    float64
 6   Adj Close  639 non-null    float64
dtypes: float64(6), object(1)
memory usage: 35.1+ KB
```

[177]:
```
df.describe()
```

[177]:
```
              High          Low         Open        Close        Volume  \
count   639.000000   639.000000   639.000000   639.000000  6.390000e+02
mean    543.362885   517.883537   531.004088   531.298030  4.819130e+07
std     340.837426   325.395864   333.534448   333.362040  3.579030e+07
min      46.896000    44.855999    45.959999    46.285999  9.800600e+06
25%     170.258003   162.379997   167.349998   164.783005  2.392195e+07
50%     620.409973   595.500000   603.880005   605.130005  3.448900e+07
75%     796.584991   767.744995   779.445007   781.304993  6.329725e+07
max    1243.489990  1217.000000  1234.410034  1229.910034  3.046940e+08

         Adj Close
count   639.000000
mean    531.298030
std     333.362040
min      46.285999
25%     164.783005
50%     605.130005
75%     781.304993
max    1229.910034
```

[178]:
```
df.columns = df.columns.str.strip()  #Remove any leading or trailing whaite␣
 ↪spaces
```

[179]:
```
print("Columns:", df.columns)
```

```
Columns: Index(['Date', 'High', 'Low', 'Open', 'Close', 'Volume', 'Adj Close'],
dtype='object')
```

Exploratory Data Analysis

[180]:
```
plt.figure(figsize=(15,5))
plt.plot(df['Close'])
```

```
plt.title('Tesla Close price.', fontsize=15)
plt.ylabel('Price in dollars.')
plt.show()
```

[181]:
```
df[df['Close'] == df['Adj Close']].shape
```

[181]: (639, 7)

[182]:
```
df = df.drop(['Adj Close'], axis=1)    #Drop columns
```

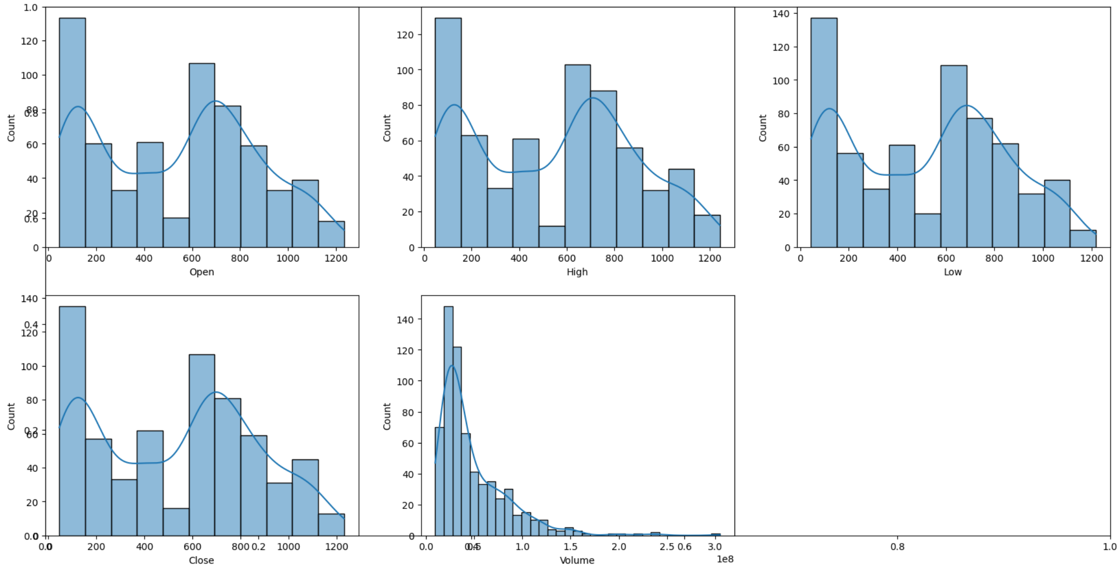
Check missing values in each column

[183]:
```
df.isnull().sum()
```

[183]:
```
Date      0
High      0
Low       0
Open      0
Close     0
Volume    0
dtype: int64
```

Plot the Histogram

[184]:
```
features = ['Open', 'High', 'Low', 'Close', 'Volume']

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

for i, col in enumerate(features):
  plt.subplot(2,3,i+1)
  sns.histplot(df[col] , kde=True)
plt.show()
```



[185]:
```
splitted = df['Date'].str.split('-', expand=True)

df['Year'] = splitted[0].astype('int')
df['Month'] = splitted[1].astype('int')
df['Day'] = splitted[2].astype('int')

df.head()
```

[185]:
```
         Date       High        Low       Open      Close      Volume  Year  \
0  2019-09-30  48.796001  47.222000  48.599998  48.174000  29399000.0  2019
1  2019-10-01  49.189999  47.826000  48.299999  48.938000  30813000.0  2019
2  2019-10-02  48.930000  47.886002  48.658001  48.625999  28157000.0  2019
3  2019-10-03  46.896000  44.855999  46.372002  46.605999  75422500.0  2019
4  2019-10-04  46.956001  45.613998  46.321999  46.285999  39975000.0  2019

   Month  Day
0      9   30
1     10    1
2     10    2
3     10    3
4     10    4
```

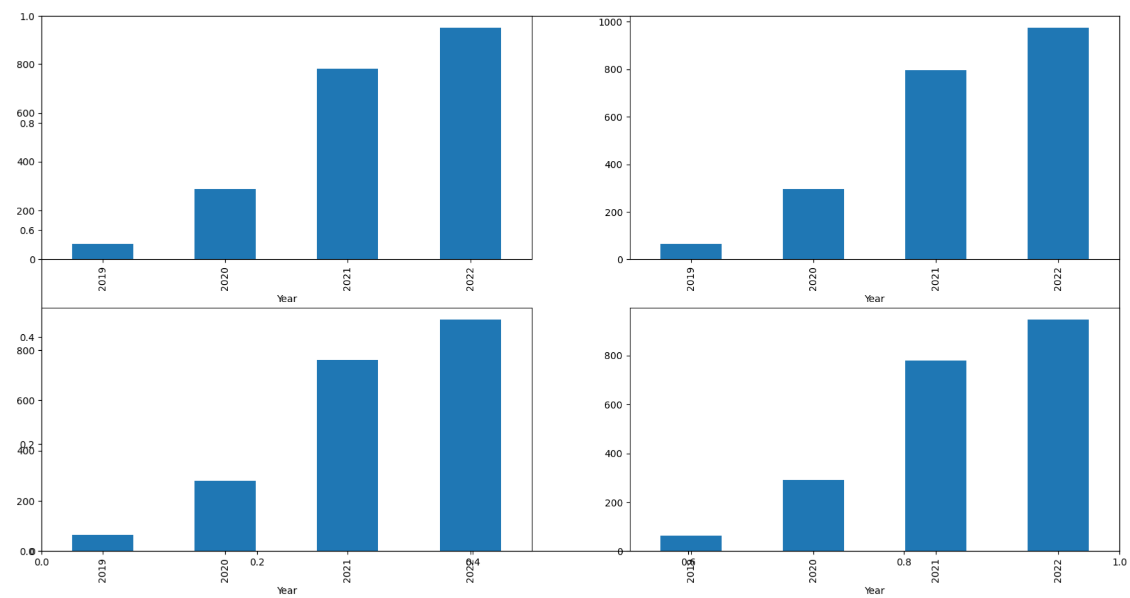
[186]:
```
df['is_quarter_end'] = np.where(df['Month']%3==0,1,0)
df.head()
```

[186]:
```
         Date       High        Low       Open      Close      Volume  Year  \
0  2019-09-30  48.796001  47.222000  48.599998  48.174000  29399000.0  2019
1  2019-10-01  49.189999  47.826000  48.299999  48.938000  30813000.0  2019
```

```
2  2019-10-02  48.930000  47.886002  48.658001  48.625999  28157000.0  2019
3  2019-10-03  46.896000  44.855999  46.372002  46.605999  75422500.0  2019
4  2019-10-04  46.956001  45.613998  46.321999  46.285999  39975000.0  2019

   Month  Day  is_quarter_end
0      9   30               1
1     10    1               0
2     10    2               0
3     10    3               0
4     10    4               0
```

Plot the mean value of the each column

[187]:
```
data_grouped = df.drop('Date', axis=1).groupby('Year').mean()
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()
```



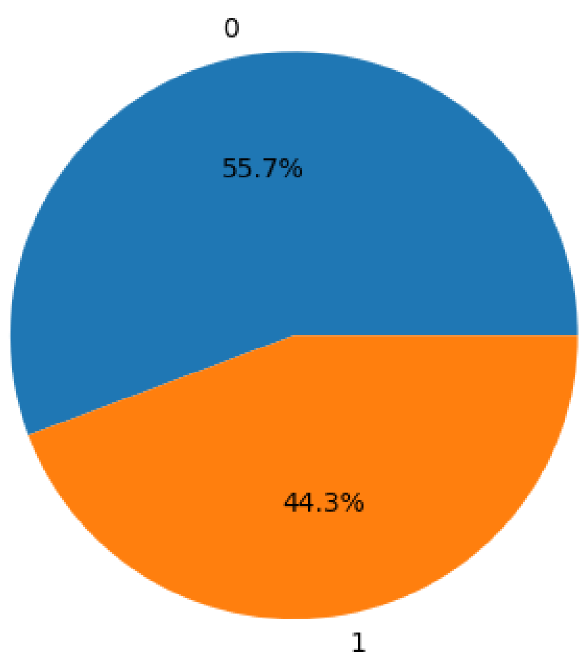
[188]:
```
df.drop('Date',axis=1).groupby('is_quarter_end').mean()
```

[188]:
```
                      High         Low        Open       Close        Volume  \
is_quarter_end
0               537.826601  512.947180  525.494497  525.656104  4.886455e+07
1               553.906989  527.285055  541.497355  542.043335  4.690906e+07
```

```
                      Year     Month        Day
is_quarter_end
0               2020.508353  6.076372  15.527446
1               2020.509091  7.431818  15.750000
```

[189]:
```python
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)  #Check next␣
↪day closing price is greater than the current day closing price
```

[190]:
```python
plt.pie(df['target'].value_counts().values,
        labels=[0, 1], autopct='%1.1f%%')
plt.show()
```



[191]:
```python
df_reset = df.reset_index()
print(df_reset.columns)
```

```
Index(['index', 'Date', 'High', 'Low', 'Open', 'Close', 'Volume', 'Year',
       'Month', 'Day', 'is_quarter_end', 'open-close', 'low-high', 'target'],
      dtype='object')
```

[192]:
```python
df_reset = df.reset_index()
print(df_reset.head())  # Shows the first few rows of the DataFrame
```

```
   index        Date       High        Low       Open      Close      Volume  \
0      0  2019-09-30  48.796001  47.222000  48.599998  48.174000  29399000.0
1      1  2019-10-01  49.189999  47.826000  48.299999  48.938000  30813000.0
2      2  2019-10-02  48.930000  47.886002  48.658001  48.625999  28157000.0
3      3  2019-10-03  46.896000  44.855999  46.372002  46.605999  75422500.0
4      4  2019-10-04  46.956001  45.613998  46.321999  46.285999  39975000.0

   Year  Month  Day  is_quarter_end  open-close  low-high  target
0  2019      9   30               1    0.425999 -1.574001       1
1  2019     10    1               0   -0.638000 -1.363998       0
2  2019     10    2               0    0.032001 -1.043999       0
3  2019     10    3               0   -0.233997 -2.040001       0
4  2019     10    4               0    0.035999 -1.342003       1
```

[193]:

```
print(df_reset.index)
```

```
RangeIndex(start=0, stop=639, step=1)
```

[194]:

```
print(df.head())  # Check the first few rows
print(df.columns)  # Ensure 'Date' is listed
```

```
        Date       High        Low       Open      Close      Volume  Year  \
0  2019-09-30  48.796001  47.222000  48.599998  48.174000  29399000.0  2019
1  2019-10-01  49.189999  47.826000  48.299999  48.938000  30813000.0  2019
2  2019-10-02  48.930000  47.886002  48.658001  48.625999  28157000.0  2019
3  2019-10-03  46.896000  44.855999  46.372002  46.605999  75422500.0  2019
4  2019-10-04  46.956001  45.613998  46.321999  46.285999  39975000.0  2019

   Month  Day  is_quarter_end  open-close  low-high  target
0      9   30               1    0.425999 -1.574001       1
1     10    1               0   -0.638000 -1.363998       0
2     10    2               0    0.032001 -1.043999       0
3     10    3               0   -0.233997 -2.040001       0
4     10    4               0    0.035999 -1.342003       1
Index(['Date', 'High', 'Low', 'Open', 'Close', 'Volume', 'Year', 'Month',
       'Day', 'is_quarter_end', 'open-close', 'low-high', 'target'],
      dtype='object')
```

[195]:

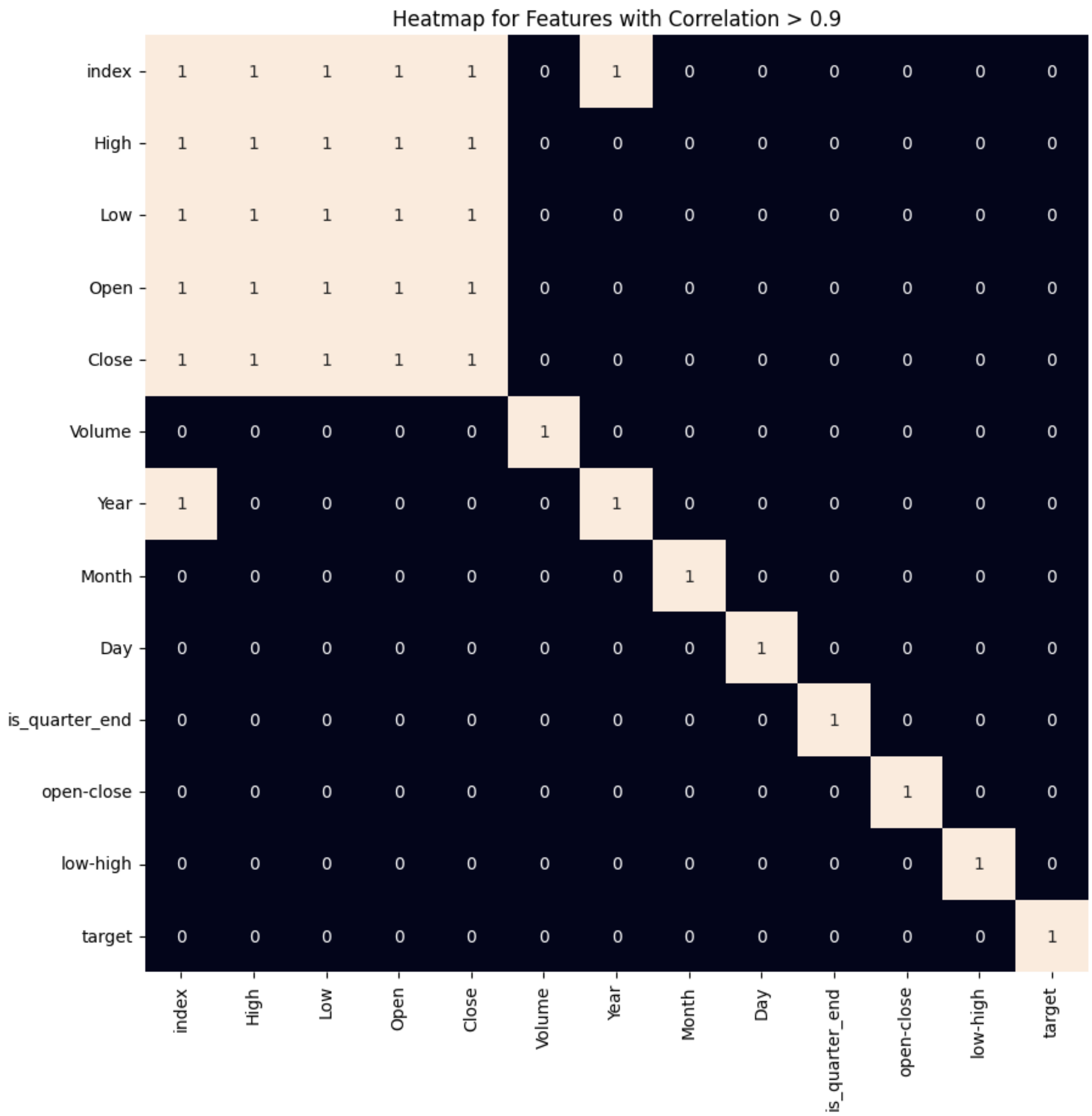
```
print([col for col in df.columns if 'Date' in col.lower()])  # Checks for␣
 ↪similar names
```

```
[]
```

[196]:

```
# Additional Heatmap for Highly Correlated Features
plt.figure(figsize=(10, 10))

# Reset the index temporarily to drop 'Date' column
df_reset = df.reset_index()
```

```python
# Generate the heatmap with correlation greater than 0.9
sns.heatmap(df_reset.drop('Date', axis=1).corr() > 0.9, annot=True, cbar=False)

plt.title('Heatmap for Features with Correlation > 0.9')
plt.show()
```



[197]:

```python
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)
```

```
(575, 3) (64, 3)
```

Feature Engineering

[198]:
```
df['Price Change'] = df['Close'] - df['Open']
df['Price Direction'] = np.where(df['Price Change'] > 0, 1, 0)
```

Adding lagged features for temporal patterns

[199]:
```
for lag in range(1, 4):  # 1-day, 2-day, 3-day lag
    df[f'Lag_Close_{lag}'] = df['Close'].shift(lag)   #Learn from past details
```

Drop rows with Nan values after adding lagged features

[200]:
```
df.dropna(inplace=True)
```

Select features and target

[201]:
```
X = df[['High', 'Low', 'Open', 'Close', 'Lag_Close_1', 'Lag_Close_2',␣
 ↪'Lag_Close_3']]
y = df['Price Direction']
```

Scale features

[202]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Train-Test Split

[203]:
```
train_size = int(len(df) * 0.7)
valid_size = int(len(df) * 0.85)
```

[204]:
```
X_train, X_valid, X_test = (
    X_scaled[:train_size],
    X_scaled[train_size:valid_size],
    X_scaled[valid_size:],
)
```

[205]:
```
y_train, y_valid, y_test = (
    y[:train_size].values,
    y[train_size:valid_size].values,
    y[valid_size:].values,
)
```

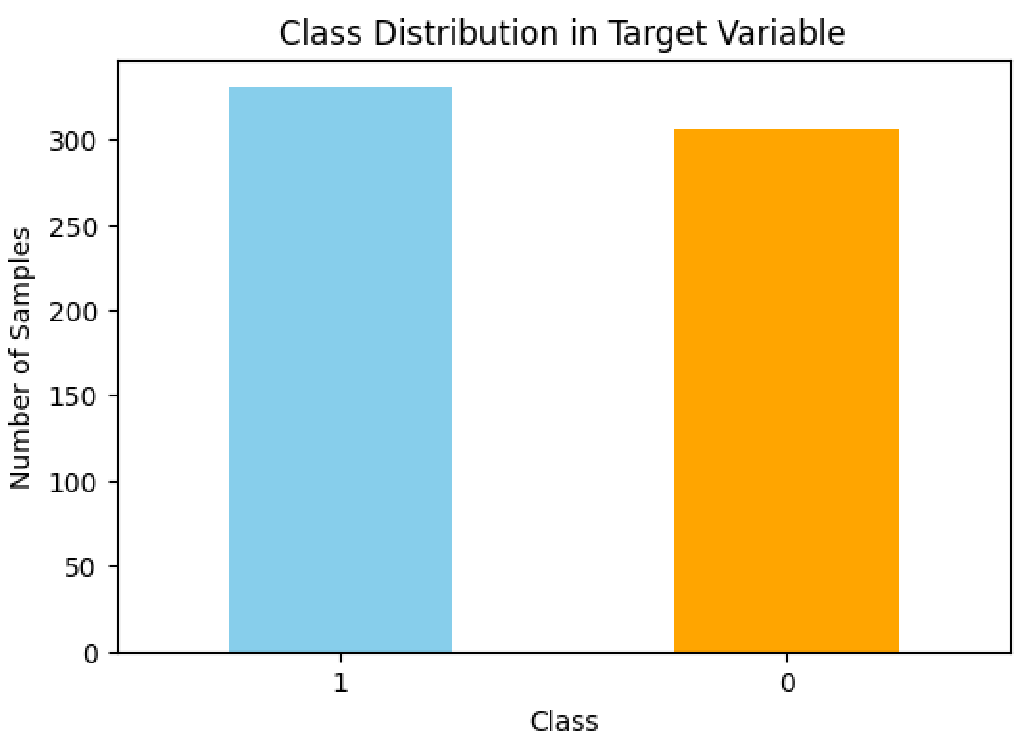
Check the class distribution

[206]:
```
class_counts = df['Price Direction'].value_counts()
print("Class Distribution:")
print(class_counts)
```

```
Class Distribution:
Price Direction
1    330
0    306
Name: count, dtype: int64
```

Visualize the class distribution

[207]:
```
plt.figure(figsize=(6, 4))
class_counts.plot(kind='bar', color=['skyblue', 'orange'])
plt.title("Class Distribution in Target Variable")
plt.xlabel("Class")
plt.ylabel("Number of Samples")
plt.xticks(rotation=0)
plt.show()
```



Calculate the imbalanced ratio

[208]:
```
imbalance_ratio = class_counts.max() / class_counts.min()
print(f"\nImbalance Ratio: {imbalance_ratio:.2f}")
```

```
Imbalance Ratio: 1.08
```

[209]:
```python
if imbalance_ratio > 1.5:
    print("The dataset is imbalanced.")
else:
    print("The dataset is balanced.")
```

```
The dataset is balanced.
```

Handle imbalance using SMOTE and Tomek Links

[210]:
```python
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
```

[211]:
```python
tomek = TomekLinks()
X_train_res, y_train_res = tomek.fit_resample(X_train_res, y_train_res) 
 ↪#Further cleaning resampling dataset
```

Logistic regression with Hyperparameter tuning

[212]:
```python
param_dist = {
    'C': uniform(0.1, 10),  #Regularization parameter
    'penalty': ['l2'],      #Regularization type
    'solver': ['lbfgs'],    #Algorithm for optimization
    'max_iter': [100, 200, 500],
    'class_weight': ['balanced', None],
}
```

TimeSeries Split for stability

[213]:
```python
tscv = TimeSeriesSplit(n_splits=5)   #Ensure trainig data always comes before
 ↪the validation data

random_search = RandomizedSearchCV(
    LogisticRegression(),
    param_distributions=param_dist,
    n_iter=50,
    cv=tscv,
    scoring='roc_auc',
    random_state=42,
    n_jobs=-1,
)
random_search.fit(X_train_res, y_train_res)
```

[213]:
```
RandomizedSearchCV(cv=TimeSeriesSplit(gap=0, max_train_size=None, n_splits=5,
test_size=None),
                   estimator=LogisticRegression(), n_iter=50, n_jobs=-1,
                   param_distributions={'C':
```

```
<scipy.stats._distn_infrastructure.rv_continuous_frozen object at
0x78690c29e290>,
                                        'class_weight': ['balanced', None],
                                        'max_iter': [100, 200, 500],
                                        'penalty': ['l2'],
                                        'solver': ['lbfgs']},
                   random_state=42, scoring='roc_auc')
```

Best model

[214]:
```
best_model = random_search.best_estimator_
print("\nBest Parameters:", random_search.best_params_)
```

```
Best Parameters: {'C': 9.75255307264138, 'class_weight': None, 'max_iter': 100,
'penalty': 'l2', 'solver': 'lbfgs'}
```

Train best model

[215]:
```
best_model.fit(X_train_res, y_train_res)
```

[215]:
```
LogisticRegression(C=9.75255307264138)
```

Validation Predictions

[216]:
```
y_pred_proba_valid = best_model.predict_proba(X_valid)[:, 1]
```

Optimize threshold based on Precision-Recall curve

[217]:
```
precision, recall, thresholds = precision_recall_curve(y_valid,
 ↪y_pred_proba_valid)
optimal_idx = np.argmax(precision * recall)
optimal_threshold = thresholds[optimal_idx]
print(f"\nOptimal Threshold: {optimal_threshold:.2f}")

y_pred_valid = (y_pred_proba_valid >= optimal_threshold).astype(int)
```

```
Optimal Threshold: 0.43
```

Classification Report (Validation)

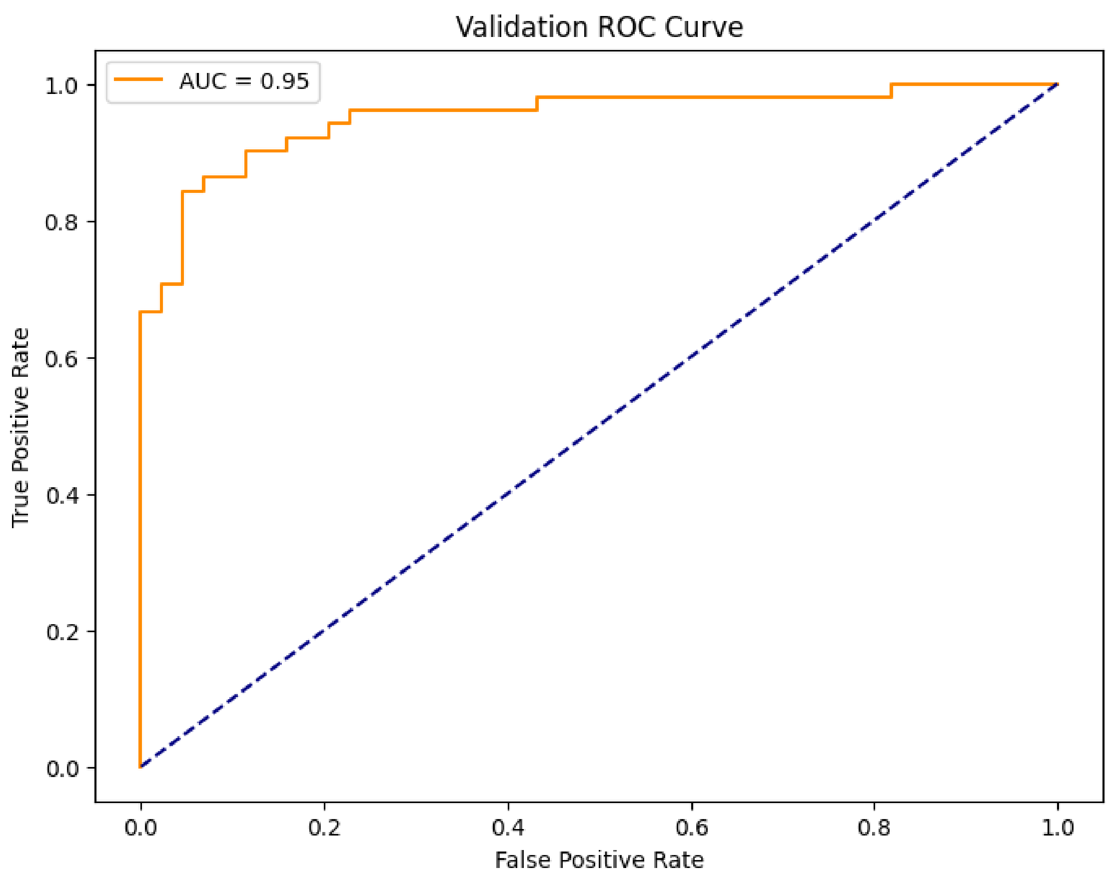
[218]:
```
print("\nValidation Classification Report:")
print(classification_report(y_valid, y_pred_valid))
```

```
Validation Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.89      0.89        44
```

```
           1       0.90      0.90      0.90        51

    accuracy                           0.89        95
   macro avg       0.89      0.89      0.89        95
weighted avg       0.89      0.89      0.89        95
```

ROC Curve (Validation)

[219]:
```python
fpr, tpr, _ = roc_curve(y_valid, y_pred_proba_valid)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'AUC = {roc_auc:.2f}', color='darkorange')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Validation ROC Curve')
plt.legend(loc='best')
plt.show()
```



Final Test Evaluation

[220]:
```
y_pred_proba_test = best_model.predict_proba(X_test)[:, 1]
y_pred_test = (y_pred_proba_test >= optimal_threshold).astype(int)

test_auc = roc_auc_score(y_test, y_pred_proba_test)
print(f"\nTest AUC: {test_auc:.4f}")

print("\nTest Classification Report:")
print(classification_report(y_test, y_pred_test))
```

```
Test AUC: 0.9961

Test Classification Report:
              precision    recall  f1-score   support

           0       0.88      1.00      0.94        45
           1       1.00      0.88      0.94        51

    accuracy                           0.94        96
   macro avg       0.94      0.94      0.94        96
weighted avg       0.94      0.94      0.94        96
```

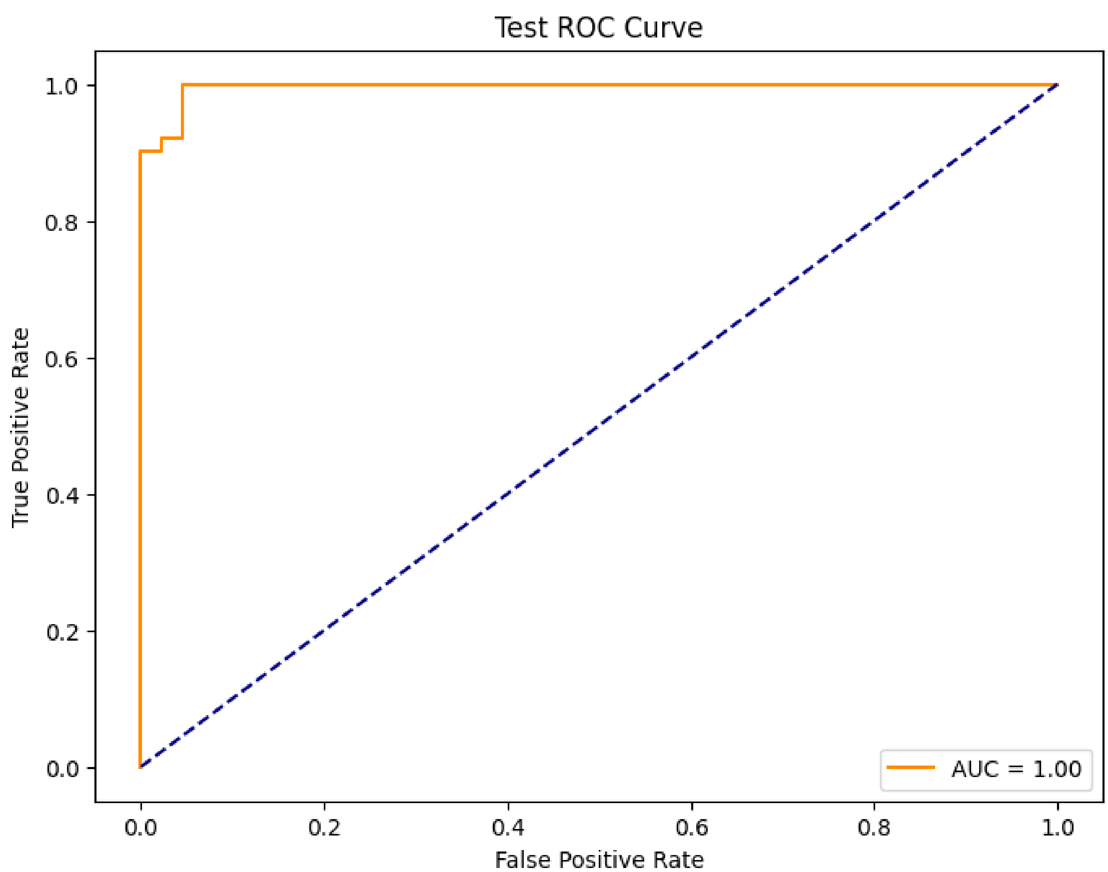
Confusion matrix (Test set)

[221]:
```
y_pred_proba_test = best_model.predict_proba(X_test)[:, 1]
y_pred_test = (y_pred_proba_test >= optimal_threshold).astype(int)

test_auc = roc_auc_score(y_test, y_pred_proba_test)
print(f"\nTest AUC: {test_auc:.4f}")

print("\nTest Classification Report:")
print(classification_report(y_test, y_pred_test))
```

```
Test AUC: 0.9961

Test Classification Report:
              precision    recall  f1-score   support

           0       0.88      1.00      0.94        45
           1       1.00      0.88      0.94        51

    accuracy                           0.94        96
   macro avg       0.94      0.94      0.94        96
weighted avg       0.94      0.94      0.94        96
```

ROC Curve (Test set)

[222]:
```
fpr_test, tpr_test, _ = roc_curve(y_test, y_pred_proba_test)
roc_auc_test = auc(fpr_test, tpr_test)

plt.figure(figsize=(8, 6))
plt.plot(fpr_test, tpr_test, label=f'AUC = {roc_auc_test:.2f}',␣
  ↪color='darkorange')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Test ROC Curve')
plt.legend(loc='best')
plt.show()
```



Precision-Recall Curve (Test Set)

[223]:
```
precision_test, recall_test, _ = precision_recall_curve(y_test,␣
  ↪y_pred_proba_test)
plt.figure(figsize=(8, 6))
```

```
plt.plot(recall_test, precision_test, label=f'AP = {auc(recall_test,␣
 ↪precision_test):.2f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Test Precision-Recall Curve')
plt.legend(loc='best')
plt.show()
```