Part 1 Data Gathering

```
# Install the required packages
! pip install beautifulsoup4
! pip install yfinance
url =
'https://launchpad.net/~mario-mariomedina/+archive/ubuntu/talib/+files
'
ext = '0.4.0-oneiric1_amd64.deb -qO'
!wget $url/libta-lib0_$ext libta.deb
!wget $url/ta-lib0-dev_$ext ta.deb
!dpkg -i libta.deb ta.deb
!pip install ta-lib
import talib
```

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Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: beautifulsoup4 in
/usr/local/lib/python3.8/dist-packages (4.11.2)
Requirement already satisfied: soupsieve>1.2 in
/usr/local/lib/python3.8/dist-packages (from beautifulsoup4) (2.4)
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: yfinance in
/usr/local/lib/python3.8/dist-packages (0.2.12)
Requirement already satisfied: pandas>=1.3.0 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (1.3.5)
Requirement already satisfied: multitasking>=0.0.7 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (0.0.11)
Requirement already satisfied: beautifulsoup4>=4.11.1 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (4.11.2)
Requirement already satisfied: requests>=2.26 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (2.28.2)
Requirement already satisfied: appdirs>=1.4.4 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (1.4.4)
Requirement already satisfied: html5lib>=1.1 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (1.1)
Requirement already satisfied: lxml>=4.9.1 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (4.9.2)
Requirement already satisfied: frozendict>=2.3.4 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (2.3.5)
Requirement already satisfied: cryptography>=3.3.2 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (39.0.1)
Requirement already satisfied: numpy>=1.16.5 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (1.21.6)
Requirement already satisfied: pytz>=2022.5 in
/usr/local/lib/python3.8/dist-packages (from yfinance) (2022.7.1)
Requirement already satisfied: soupsieve>1.2 in
/usr/local/lib/python3.8/dist-packages (from beautifulsoup4>=4.11.1-
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>yfinance) (2.4)
Requirement already satisfied: cffi>=1.12 in
/usr/local/lib/python3.8/dist-packages (from cryptography>=3.3.2-
>yfinance) (1.15.1)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.8/dist-packages (from html5lib>=1.1->yfinance)
(0.5.1)
Requirement already satisfied: six>=1.9 in
/usr/local/lib/python3.8/dist-packages (from html5lib>=1.1->yfinance)
(1.15.0)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.8/dist-packages (from pandas>=1.3.0->yfinance)
(2.8.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.8/dist-packages (from requests>=2.26->yfinance)
(2.10)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.8/dist-packages (from requests>=2.26->yfinance)
(3.0.1)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/usr/local/lib/python3.8/dist-packages (from requests>=2.26->yfinance)
(1.24.3)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.8/dist-packages (from requests>=2.26->yfinance)
(2022.12.7)
Requirement already satisfied: pycparser in
/usr/local/lib/python3.8/dist-packages (from cffi>=1.12-
>cryptography>=3.3.2->yfinance) (2.21)
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installed.)
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Unpacking libta-lib0 (0.4.0-oneiric1) over (0.4.0-oneiric1) ...
Preparing to unpack ta.deb ...
Unpacking ta-lib0-dev (0.4.0-oneiric1) over (0.4.0-oneiric1) ...
Setting up libta-lib0 (0.4.0-oneiric1) ...
Setting up ta-lib0-dev (0.4.0-oneiric1) ...
Processing triggers for man-db (2.9.1-1) ...
Processing triggers for libc-bin (2.31-0ubuntu9.9) ...
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: ta-lib in
/usr/local/lib/python3.8/dist-packages (0.4.25)
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-
packages (from ta-lib) (1.21.6)
```

```python
from bs4 import BeautifulSoup as bs
import requests
import yfinance as yf
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

```python
import pandas as pd
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay ,
classification_report
import numpy as np
import pandas_datareader as pdr
import datetime as dt
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, roc_auc_score
import seaborn as sns



#@title functions
FEATURES_SIZE = 180
LABELLING_SIZE = 90

def calculate_returns(x):
  return 100*(x.iloc[-1]['Close'] - x.iloc[0]['Open'])/x.iloc[0]
['Open']

def get_features_labels_from_full_dataframe(df,
start_train_features_day = 0, featutes_size=FEATURES_SIZE,
labeling_size = LABELLING_SIZE):
  end_train_features_day = start_train_features_day + featutes_size
  start_train_labelling_day = end_train_features_day + 1
  end_train_labelling_day = start_train_labelling_day + labeling_size

  print(f'start_date:{start_train_features_day} , end_ft_day:
{end_train_features_day}\
        start_lbl_date:{start_train_labelling_day} , end_lbl_day:
{end_train_labelling_day}')

  features_train_df = df[(df['t0'] >=
start_train_features_day)&(df['t0'] < end_train_features_day)]
  labelling_train_df = df[(df['t0'] >=
start_train_labelling_day)&(df['t0'] < end_train_labelling_day)]
  return features_train_df, labelling_train_df

def add_label_to_labelling_df(labelling_train_df):
  lbl_returns = labelling_train_df.groupby('stock').apply(lambda x:
calculate_returns(x)).reset_index()
  lbl_returns.columns = ['stock', 'pct_price_movement']
  threshold = lbl_returns['pct_price_movement'].median()
  lbl_returns['label'] = lbl_returns['pct_price_movement']>threshold
  return lbl_returns.set_index('stock')

def calculate_featurs(features_train_df):
  features_df = features_train_df.copy()
  features_df['month_index'] = (features_df['t0'] / 30).astype(int)
  monthly_features_df =
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features_df.groupby(['stock','month_index']).apply(calculate_returns).
reset_index()
  worst_monthly_return =
monthly_features_df.groupby('stock').min().reset_index()
  best_monthly_return =
monthly_features_df.groupby('stock').max().reset_index()
  ft_df = best_monthly_return[['stock',0]]
  ft_df['worst'] = worst_monthly_return[0]
  ft_df.columns = ['stock', 'best_month', 'worst_month']
  return ft_df.set_index('stock')


def add_actual(test_df,all_labelling_test_df):
  test_returns = all_labelling_test_df.groupby('stock').apply(lambda
x:calculate_returns(x))
  label_threshold = test_returns.median()
  good_test = test_returns[test_returns > label_threshold].index
  test_df.loc[test_df['stock'].isin(good_test),'actual_y'] = 1
  test_df['actual_y'].fillna(0,inplace=True)
  test_df['actual_y'].value_counts()
  return test_df

def Get_Monthly(all_features_test_df):
  features_df2 = all_features_test_df.copy()
  features_df2['month_index'] = (features_df2['t0'] / 30).astype(int)
  return
features_df2.groupby(['stock','month_index']).apply(calculate_returns)
.reset_index()


def Confusion_and_Report(df):
  true_positive = len(df[(df['predicted_y'] ==
df['actual_y'])&(df['predicted_y']==True)])
  true_negative = len(df[(df['predicted_y'] ==
df['actual_y'])&(df['predicted_y']==False)])
  false_positive = len(df[(df['predicted_y'] !=
df['actual_y'])&(df['predicted_y']==True)])
  false_negative = len(df[(df['predicted_y'] !=
df['actual_y'])&(df['predicted_y']==False)])
  print(
        f'''
        Train results:
          True positive: {true_positive},
          True negative: {true_negative},
          False positive: {false_positive},
          False negative: {false_negative}


        ''')
  matrix = confusion_matrix(df['actual_y'], df['predicted_y'])
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  disp = ConfusionMatrixDisplay(matrix, display_labels=[0,1])
  disp.plot(cmap=plt.cm.Blues)

  plt.show()

  report = classification_report(df['actual_y'], df['predicted_y'])
  print(report)

def Get_ROC(df):

  fpr, tpr, thresholds = roc_curve(df['actual_y'], df['predicted_y'])
  # Plot the ROC curve
  print(roc_auc_score(df['actual_y'], df['predicted_y']))
  plt.plot(fpr, tpr)
  # Add the luck line
  plt.plot([0, 1], [0, 1], linestyle='--')
  plt.xlabel("False Positive Rate")
  plt.ylabel("True Positive Rate")
  plt.legend(['1st time period ','Random guess'])
  plt.title("ROC Curve")
  plt.show()
```

#download online

```
resp = requests.get('http://en.wikipedia.org/wiki/List_of_S
%26P_500_companies')
soup = bs(resp.text, 'lxml')
table = soup.find('table', {'class': 'wikitable sortable'})

tickers = []
for row in table.findAll('tr')[1:]:
    ticker = row.findAll('td')[0].text
    tickers.append(ticker)
all_stocks = [x.replace('\n','') for x in tickers] # remove the new
line character

all_df = pd.DataFrame()
start_date = '2018-07-01'
end_date = '2022-09-01'
fname_string = 'all_stocks_' + start_date + '_' + end_date + '.csv'


for tkr in all_stocks:
  single_stock_pd = yf.download(tickers=tkr, start=start_date,
end=end_date,auto_adjust=True)
  single_stock_pd['stock'] = tkr
  all_df = all_df.append(single_stock_pd)


all_df = (
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          all_df
          .reset_index()
          .assign(dt = lambda d:pd.to_datetime(d['Date']),
                  t0 = lambda d:(d['dt'] -
d['dt'].min()).dt.days.astype(float))
          )

all_df.to_csv(fname_string)
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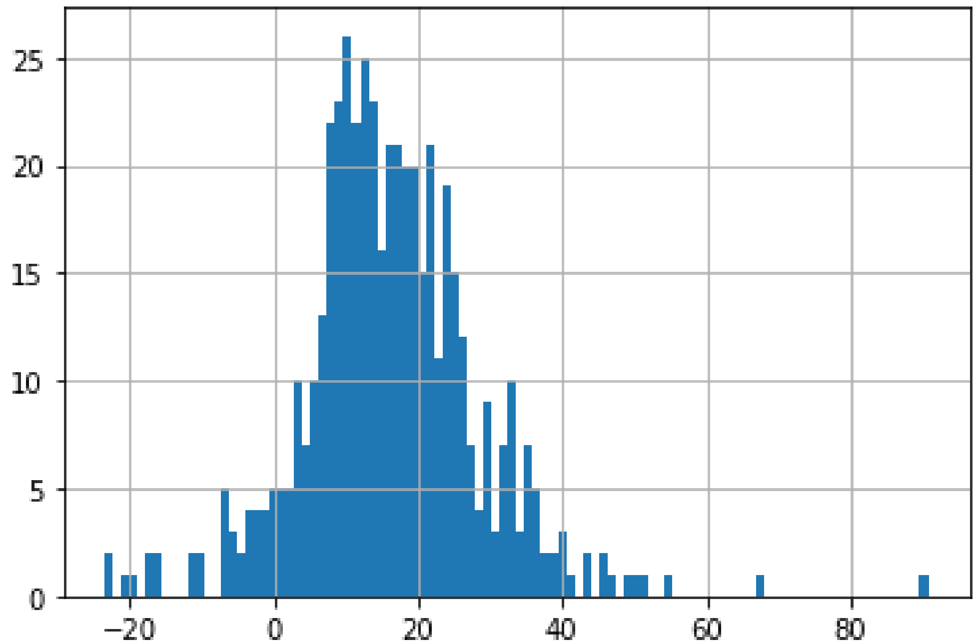
Calculate Features & Target values for all stocks

```
all_features_train_df,all_labelling_train_df =
get_features_labels_from_full_dataframe(all_df)
```

```
start_date:0 , end_ft_day: 180        start_lbl_date:181 ,
end_lbl_day: 271
```

```
# Calculating the train returns in the labelling 3 months
train_returns = all_labelling_train_df.groupby('stock').apply(lambda
x: calculate_returns(x))
train_returns.hist(bins=100)
print(train_returns)
```

```
stock
A       21.163711
AAL     -0.758539
AAP      9.319021
AAPL    20.333468
ABBV   -10.940587
          ...
YUM      9.225103
ZBH     24.167312
ZBRA    33.399114
ZION    12.829643
ZTS     18.293428
Length: 495, dtype: float64
```




```
# Splitting the stocks to good and bad stocks based on greater or less
then the median return

threshold = train_returns.median()
good = train_returns[train_returns>threshold].index
bad = train_returns[train_returns<threshold].index
```

Calculating features for the train features months

##From yigal

```
#@title Creating a monthly df for calculations
features_df = all_features_train_df.copy()
labelling_df = all_labelling_train_df.copy()
features_df['month_index'] = (features_df['t0'] / 30).astype(int)
monthly_features_df =
features_df.groupby(['stock','month_index']).apply(calculate_returns).
reset_index()

#@title Calculating each stock best and worst monthly return to be
used as our features
worst_monthly_return =
monthly_features_df.groupby('stock').min().reset_index()
best_monthly_return =
monthly_features_df.groupby('stock').max().reset_index()
train_df = best_monthly_return[['stock',0]]
train_df['worst'] = worst_monthly_return[0]
train_df.columns = ['stock', 'best_month', 'worst_month']
```

##Our Features

```
#@title all features

def indexReturn(df,features_df):
    sumOpen = features_df.groupby('stock')['Open'].first().sum()
    sumClose = features_df.groupby('stock')['Close'].last().sum()
    return (df
            .assign(IndexReturn = 100*(sumClose-sumOpen)/sumOpen)
            )

def total_yield(df,features_df):
    total_yield = (
                  features_df
                  .groupby('stock')
                  .apply(calculate_returns)
                  .reset_index()
                  [0]
                  )
    return df.assign(total_yield = total_yield.values)

def Revenue_To_Index(df):
    return (
            df
            .assign(ComparedToIndex = df['total_yield']-
df['IndexReturn'])
            .drop('IndexReturn',axis = 1)
            )

def Add_Avg_Volumn(df,features_df):
  VolumeSeries = (
                features_df
                .assign(avg_Volume =
features_df['Volume'].rolling(window=180).mean())
                .pipe(lambda d:d.groupby('stock')
['avg_Volume'].mean())
                )
  return (
          df
          .assign(avg_Volume = VolumeSeries.values)
          .pipe(lambda d:d.fillna({'avg_Volume':-999}))
          )


def Get_perc_of_profit(df,features_df):
  features_df['days_of_profit'] = features_df['Close'] >
features_df['Open']
  count_profit_days = (
                      features_df
                      .query('days_of_profit>0')
```

```
                      .groupby('stock')
                      ['days_of_profit']
                      .count()
                      )
  count_days = (
                features_df
                .groupby('stock')
                ['t0']
                .count()
                )
  return df.assign(percDaysOfProfit =
count_profit_days.div(count_days,fill_value=-999).values)


def Get_SMA(df,features_df):
  f =  (
      features_df
      .assign(sma10 = features_df["Close"].rolling(window=10).mean(),
           sma30 = features_df["Close"].rolling(window=30).mean(),
           sma50 = features_df["Close"].rolling(window=50).mean())
        )

  return df.assign(sma10 = f.groupby('stock')['sma10'].mean().values,
                   sma30 = f.groupby('stock')['sma30'].mean().values,
                   sma50 = f.groupby('stock')['sma50'].mean().values)

def Get_RSI(df,features_df):
  change = features_df["Close"].diff()
  change_up = change.copy()
  change_down = change.copy()
  change_up[change_up<0] = 0
  change_down[change_down>0] = 0
  avg_up = change_up.rolling(14).mean()
  avg_down = change_down.rolling(14).mean().abs()
  features_df=features_df.assign(rsi=( 100 * avg_up / (avg_up +
avg_down)).values)
  return df.assign(RSI=features_df.groupby('stock')
['rsi'].mean().values)

def Get_std_monthly(df,monthly_features_df):
  return (
          df
          .assign(std = monthly_features_df.groupby('stock')
[0].std().values)
          .fillna({'std':0})
          )

def Get_Bollinger(df):
  return df.assign(bb_upper = df['sma30'] + (df['std'] * 2),
                   bb_lower = df['sma30'] - (df['std'] * 2)
```

```
                   )

def Get_Beta(df,features_df):
  f = features_df.assign(Beta = talib.BETA(features_df['High'],
features_df['Low'], timeperiod=30))
  return (
          df
          .assign(Beta=f.groupby('stock')['Beta'].mean().values)
          .fillna({'Beta':-999})
          )
def Get_ATR(df,features_df):
  f = features_df.assign(ATR = talib.ATR(features_df['High'],
features_df['Low'], features_df['Close'], timeperiod=14))
  return (
          df
          .assign(ATR=f.groupby('stock')['ATR'].mean().values)
          .fillna({'ATR':-999})
          )
def Get_adx(df,features_df):
  f = features_df.assign(adx = talib.ADX(features_df['High'],
features_df['Low'], features_df['Close'], timeperiod=180))
  return (df
          .assign(adx = f.groupby('stock')['adx'].mean().values)
          .fillna({'adx':-999})
          )

def Get_all_features(df,features_df,monthly_features_df):
    return (
            df
            .pipe(lambda d:indexReturn(d,features_df))
            .pipe(lambda d:total_yield(d,features_df))
            .pipe(lambda d:Revenue_To_Index(d))
            .pipe(lambda d:Add_Avg_Volumn(d,features_df))
            .pipe(lambda d:Get_perc_of_profit(d,features_df))
            .pipe(lambda d:Get_SMA(d,features_df))
            .pipe(lambda d:Get_RSI(d,features_df))
            .pipe(lambda d:Get_std_monthly(d,monthly_features_df))
            .pipe(lambda d:Get_Bollinger(d))
            .pipe(lambda d:Get_Beta(d,features_df))
            .pipe(lambda d:Get_ATR(d,features_df))
            .pipe(lambda d:Get_adx(d,features_df))
          )

#@title Adding a binary target column for our classification based on
the labelling
train_df = (
            Get_all_features(train_df,features_df,monthly_features_df)
            .assign(target = lambda
d:np.where(d['stock'].isin(good),1,0))
```

```
            )
train_df['target'].value_counts()
```

```
1    247
0    245
Name: target, dtype: int64
```

Training the model

```
#@title Check for NA
train_df.loc[:, train_df.isna().any()]
```

```
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17,
18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51,
52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68,
69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85,
86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, ...]

[492 rows x 0 columns]
```

```
# Training a Random Forest ML model to predict if the stock return
will be above the median return in the labelling period

from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(max_depth=3, random_state=0)
clf.fit(train_df.drop(['stock','target'],axis=1), train_df['target'])
```

```
RandomForestClassifier(max_depth=3, random_state=0)
```

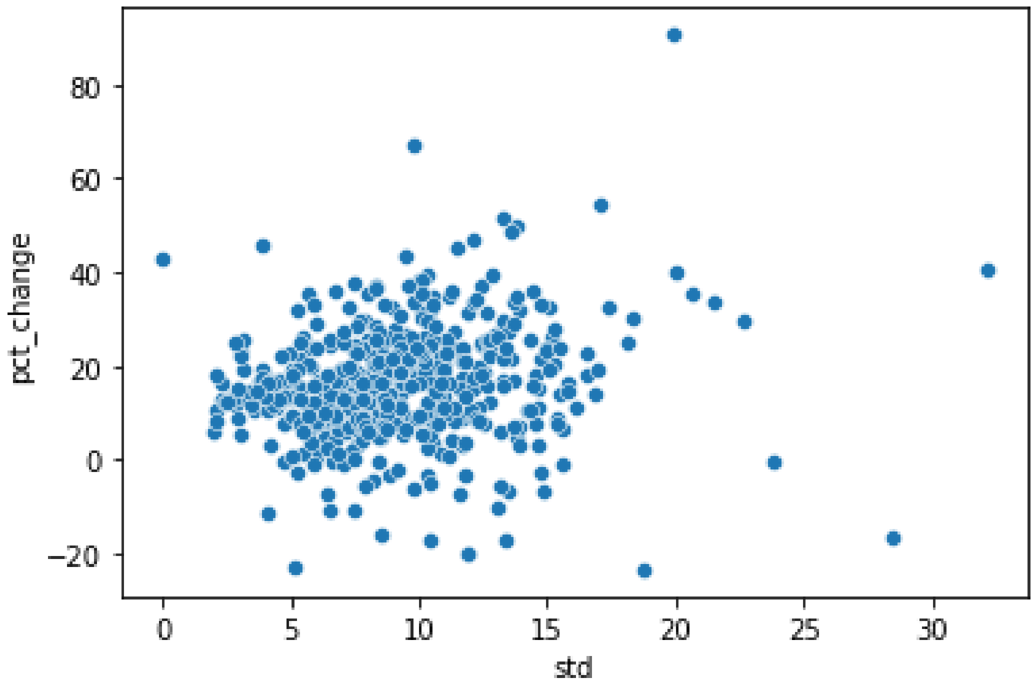
#Final Task

##First Assignment

####1.1

```
feature_chosen = 'std'
reg_df = (
          train_df
          [['stock',feature_chosen]]
          .merge(train_returns.to_frame().reset_index(),on='stock')
          .set_index('stock')
          .rename(columns={0:'pct_change'})
          )
sns.scatterplot(x=feature_chosen, y='pct_change',data=reg_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f461223c4f0>
```




```
from sklearn.linear_model import LinearRegression
from scipy.stats import pearsonr

correlation, pvalue = pearsonr(reg_df[feature_chosen],
reg_df['pct_change'])

# Print the correlation
print(f"Correlation: {correlation}")

x = np.array(reg_df[feature_chosen]).reshape(-1,1)
y = np.array(reg_df['pct_change'])

reg = LinearRegression().fit(x, y)
print(f"Intercept: {reg.intercept_} \
       \nCoefficient: {reg.coef_[0]}")
```

```
Correlation: 0.1663926174215306
Intercept: 11.412172078779047
Coefficient: 0.5249952198830796
```

###1.2 Creating a new label system(instead of pct_returns)

```
threshold = reg_df[feature_chosen].median()

good = reg_df.query(f'{feature_chosen} > @threshold').index
bad = reg_df.query(f'{feature_chosen} < @threshold').index

new_train = (
            train_df
```

```
            .drop('target',axis=1)
            .assign(target=np.where(train_df['stock'].isin(good),1,0))
            )
```

```
clf = RandomForestClassifier(max_depth=3, random_state=0)
clf.fit(new_train.drop(['stock','target'],axis=1),
new_train['target'])
```

```
RandomForestClassifier(max_depth=3, random_state=0)
```

```
all_features_test_df,all_labelling_test_df =
get_features_labels_from_full_dataframe(all_df,start_train_features_da
y = 270)
features_df2 = all_features_test_df.copy()
monthly_features_df2 = Get_Monthly(all_features_test_df)
new_test = calculate_featurs(all_features_test_df).reset_index()
new_test = Get_all_features(new_test, features_df2,
monthly_features_df2)
```

```
start_date:270 , end_ft_day: 450        start_lbl_date:451 ,
end_lbl_day: 541
```

####Statistical Difference

```
good_stocks = new_train[new_train['target'] == True]
bad_stocks = new_train[new_train['target'] == False]
```

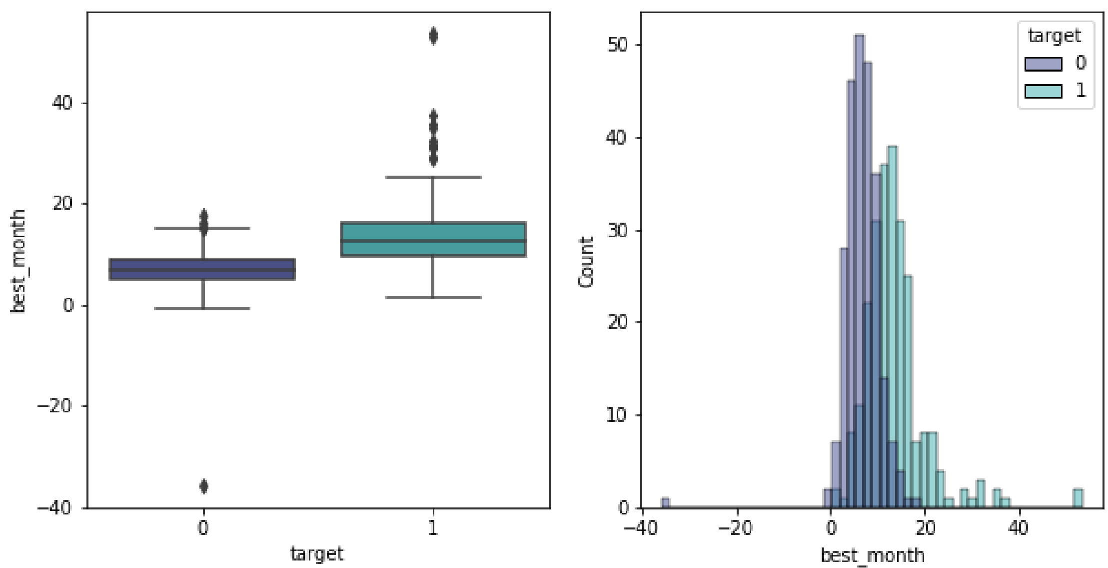
```
from scipy.stats import mannwhitneyu
for feature in
new_train.drop(['stock',feature_chosen,'target'],axis=1).columns:
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))

    sns.boxplot(x='target', y=feature, data=new_train,
palette='mako',ax=ax1)
    sns.histplot(x=feature,
data=new_train,palette='mako',hue='target',ax=ax2)

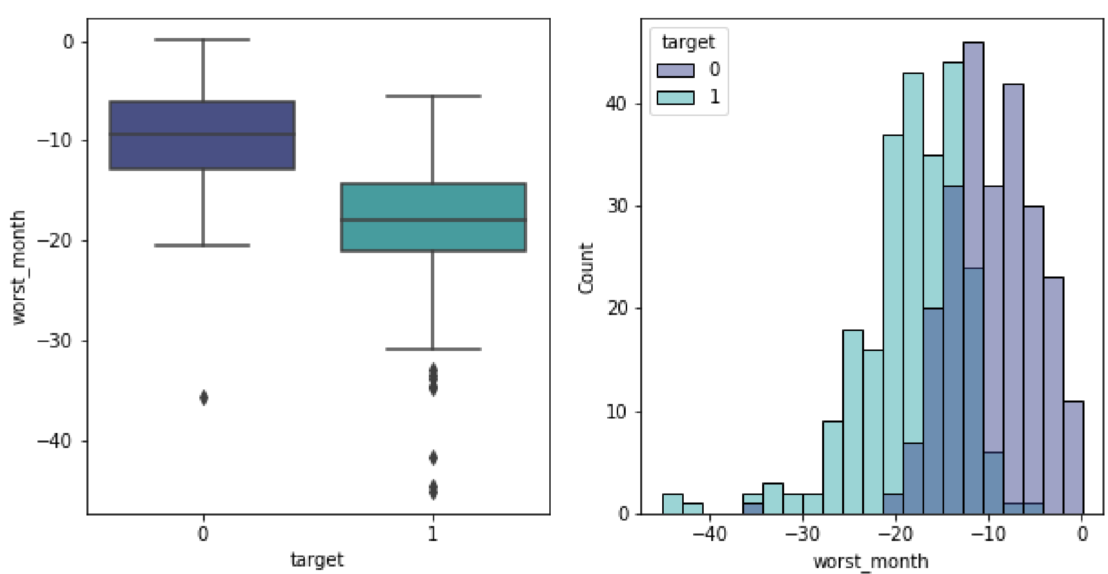
    statistic, pvalue = mannwhitneyu(good_stocks[feature],
bad_stocks[feature])
    if pvalue < 0.05:
        print(f'\033[1mThere is a significant difference in the
distribution of {feature} between the True and False groups (p-value =
{pvalue:.3f})\033[0m')
    else:
        print(f'\033[1mThere is no significant difference in the
distribution of {feature} between the True and False groups (p-value =
{pvalue:.3f})\033[0m')
    print()

    plt.show()
```

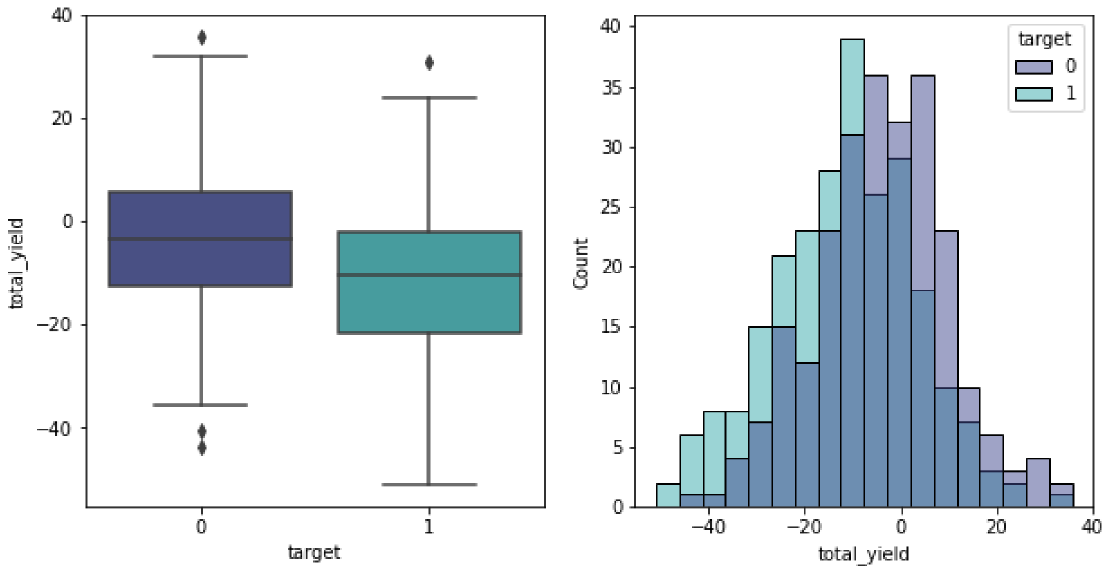
```
There is a significant difference in the distribution of best_month
between the True and False groups (p-value = 0.000)
```



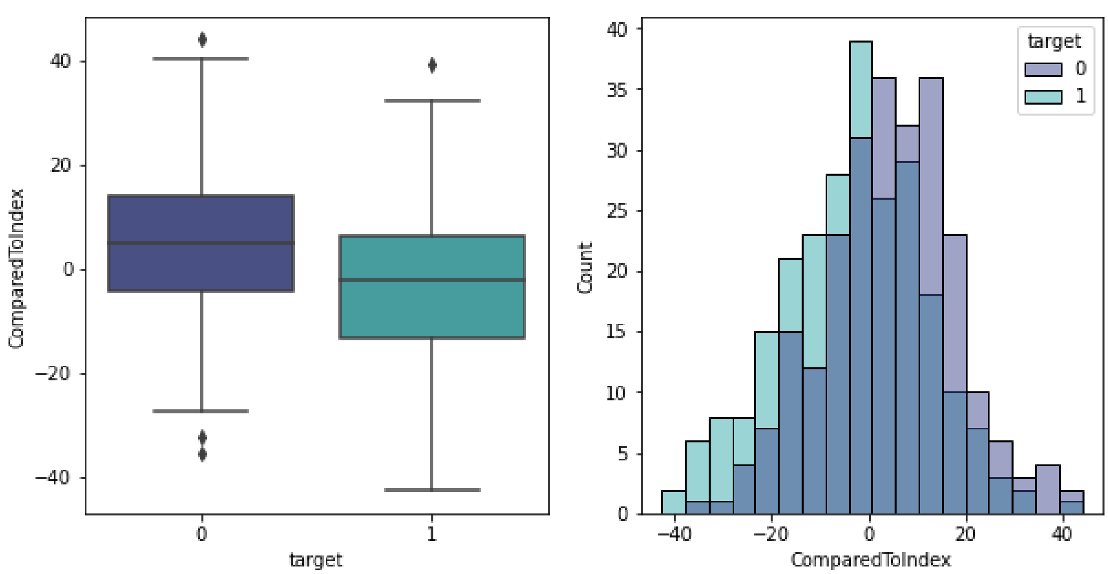

```
There is a significant difference in the distribution of worst_month
between the True and False groups (p-value = 0.000)
```



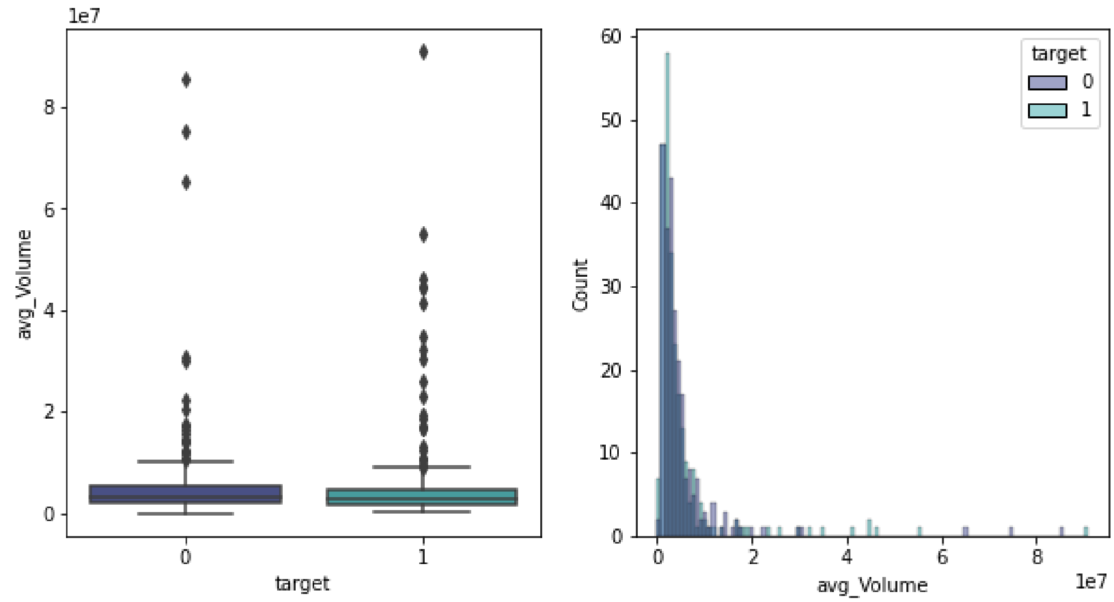

```
There is a significant difference in the distribution of total_yield
between the True and False groups (p-value = 0.000)
```



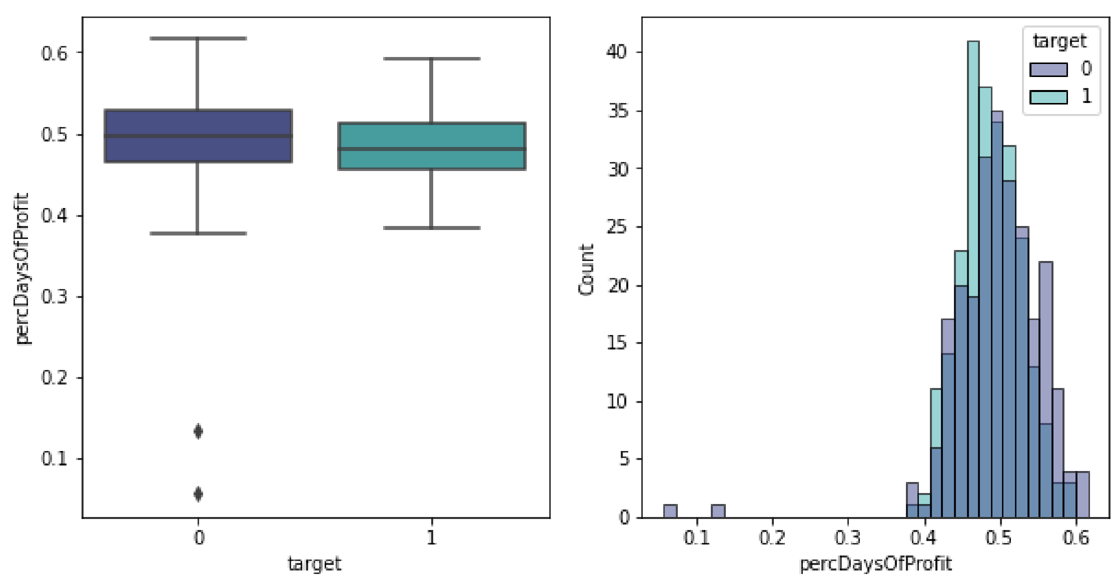
There is a significant difference in the distribution of ComparedToIndex between the True and False groups (p-value = 0.000)



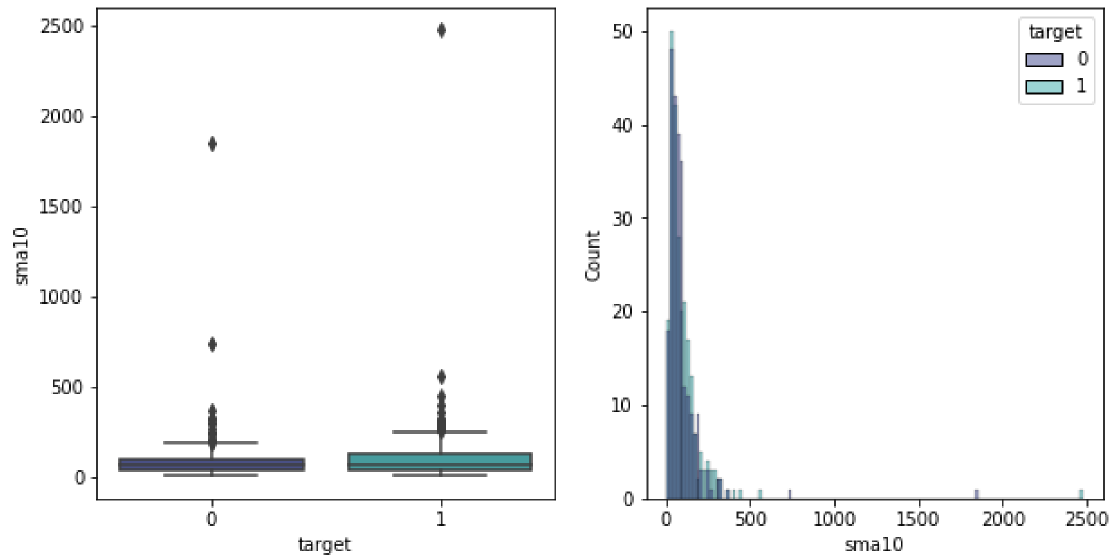
There is no significant difference in the distribution of avg_Volume between the True and False groups (p-value = 0.085)



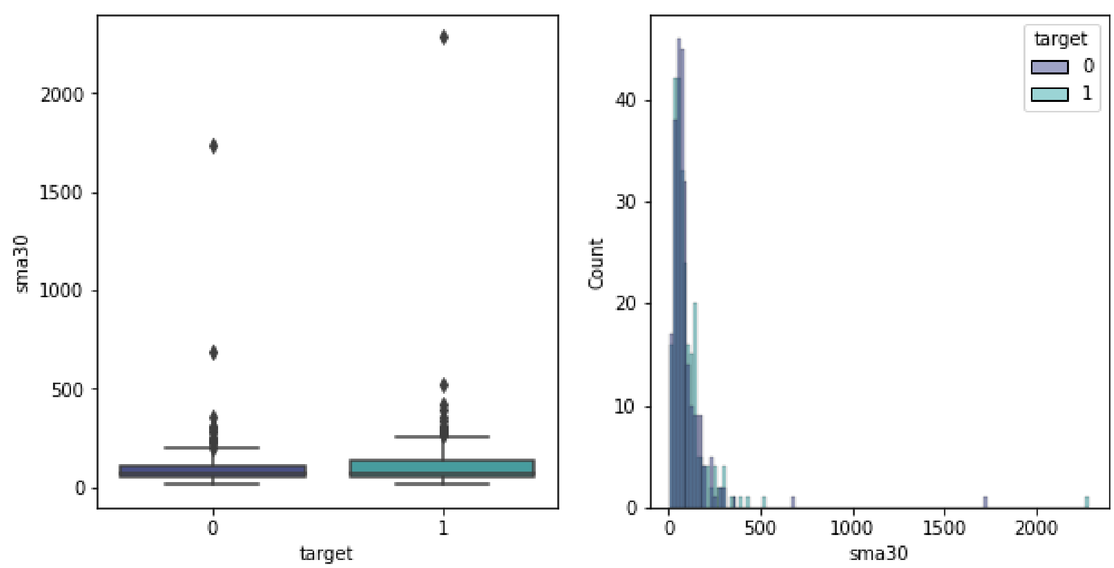

```
There is a significant difference in the distribution of
percDaysOfProfit between the True and False groups (p-value = 0.002)
```



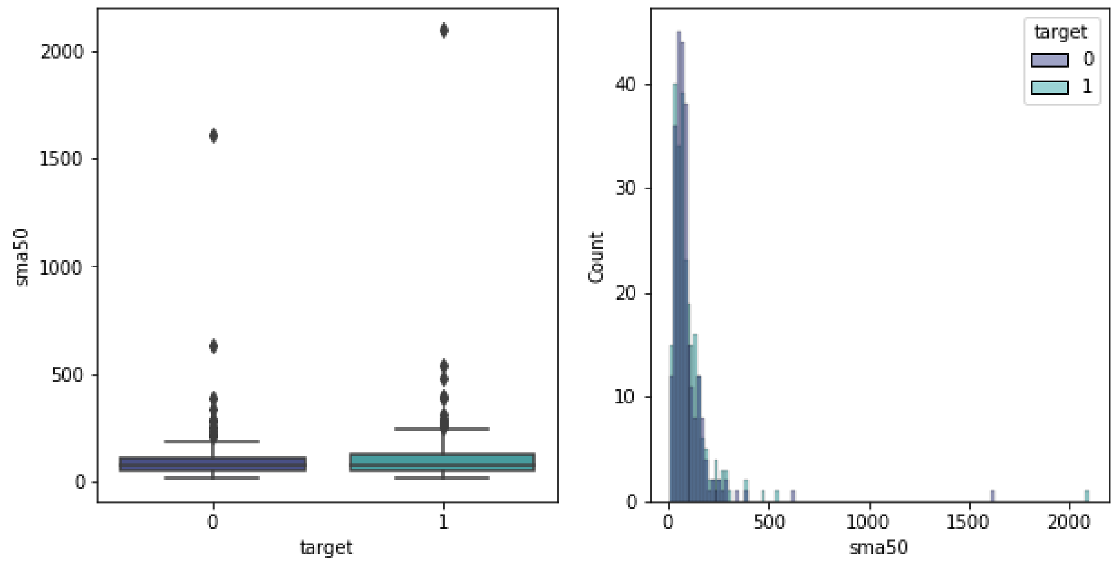

```
There is no significant difference in the distribution of sma10
between the True and False groups (p-value = 0.426)
```



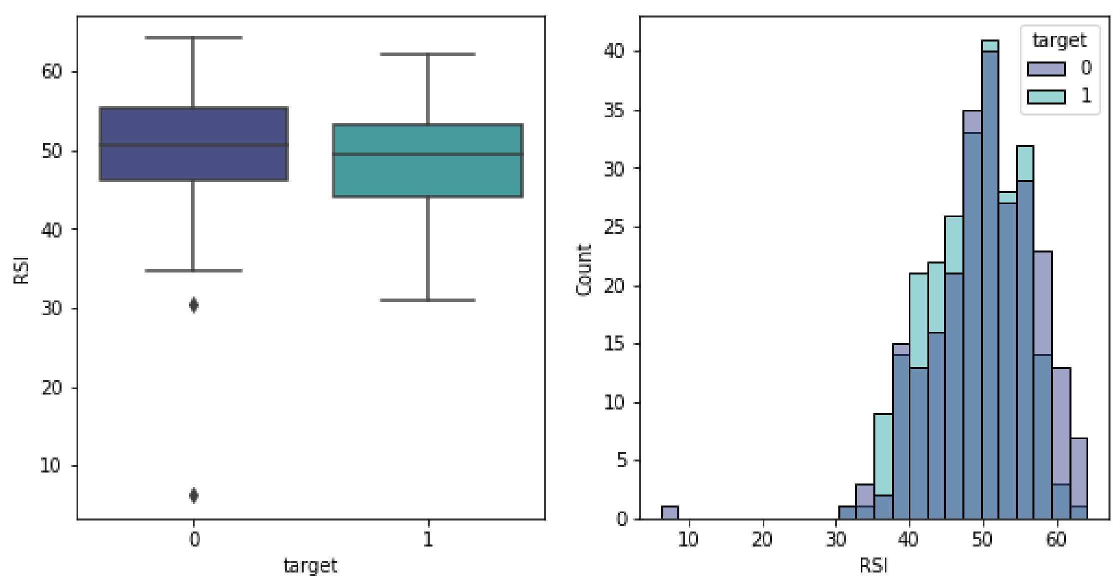

```
There is no significant difference in the distribution of sma30
between the True and False groups (p-value = 0.351)
```



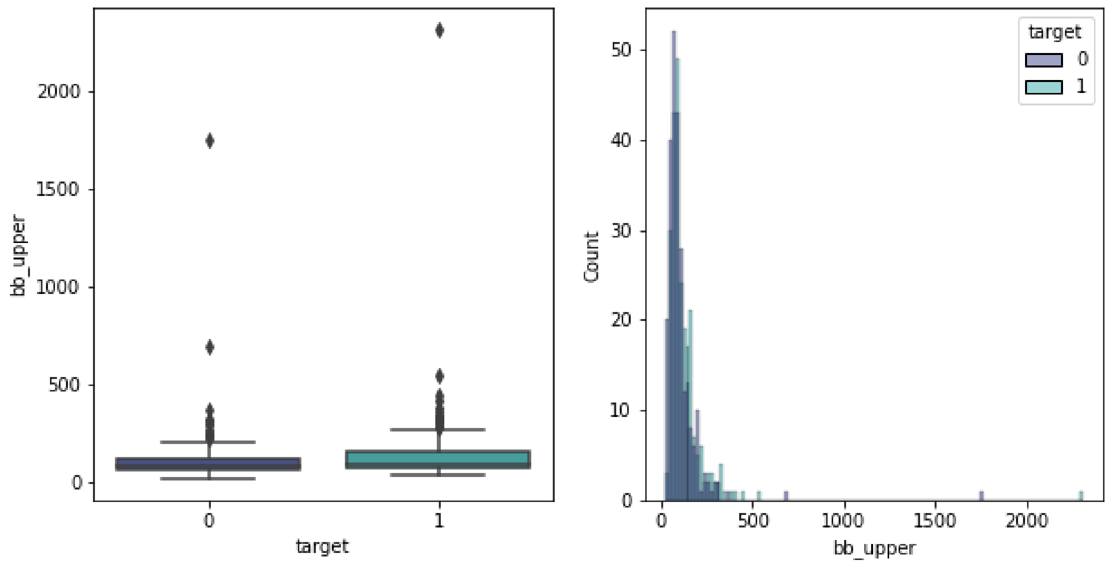

```
There is no significant difference in the distribution of sma50
between the True and False groups (p-value = 0.251)
```



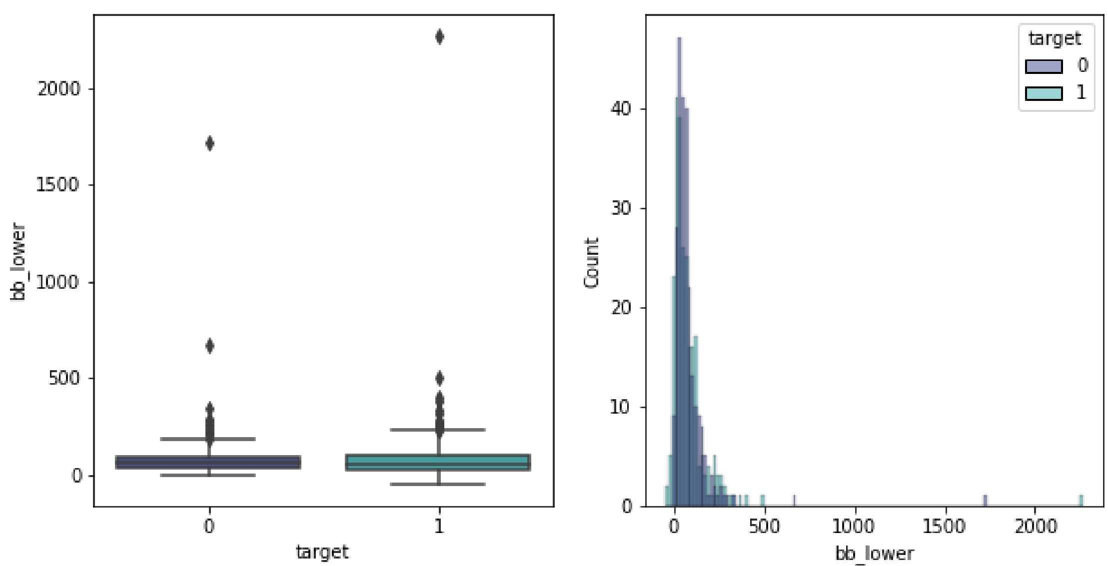

```
There is a significant difference in the distribution of RSI between
the True and False groups (p-value = 0.004)
```



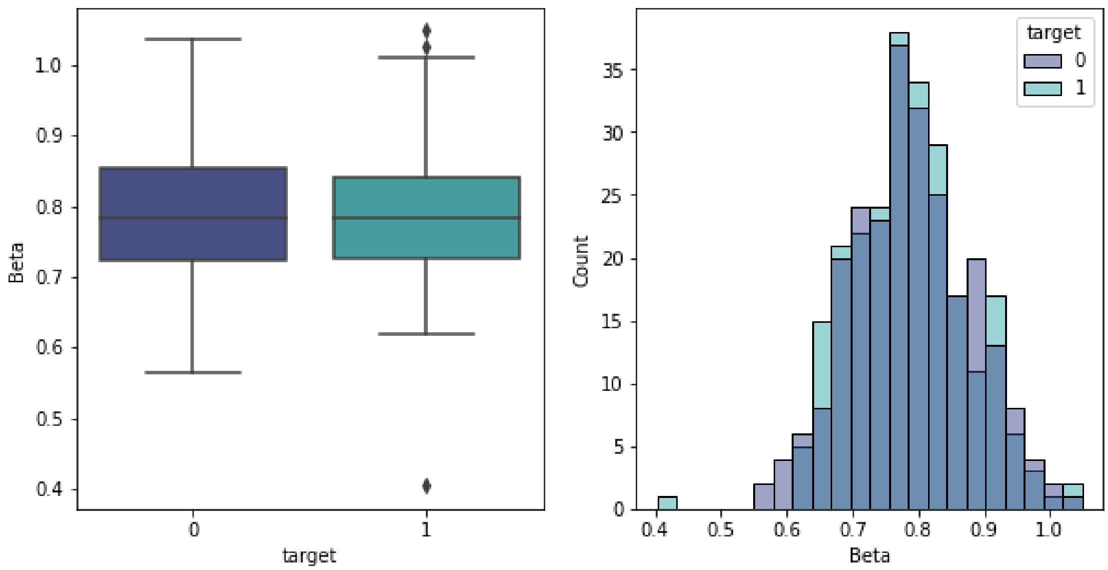

```
There is a significant difference in the distribution of bb_upper
between the True and False groups (p-value = 0.000)
```



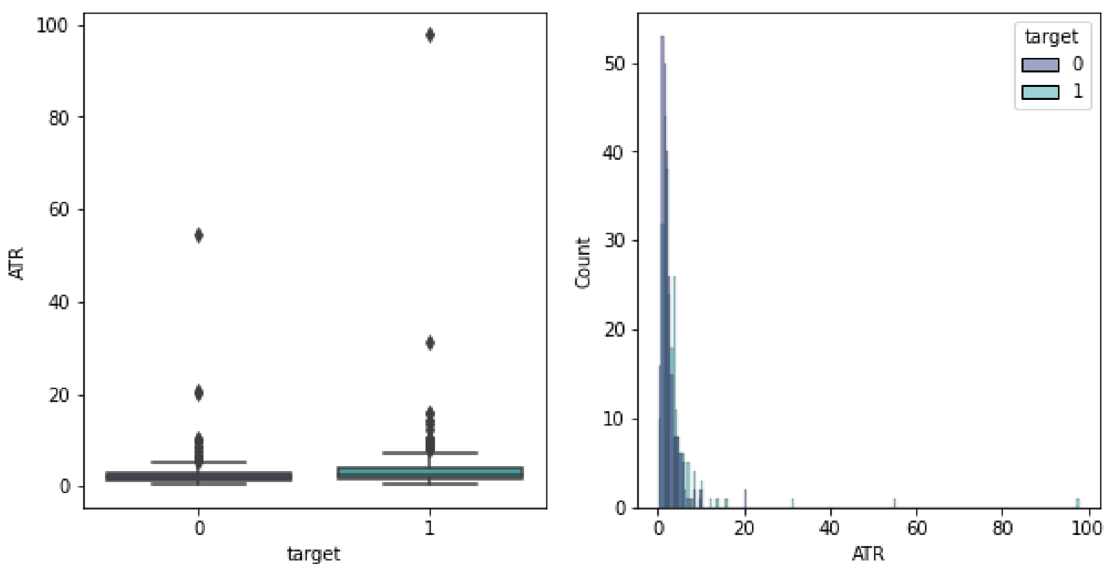

```
There is no significant difference in the distribution of bb_lower
between the True and False groups (p-value = 0.072)
```



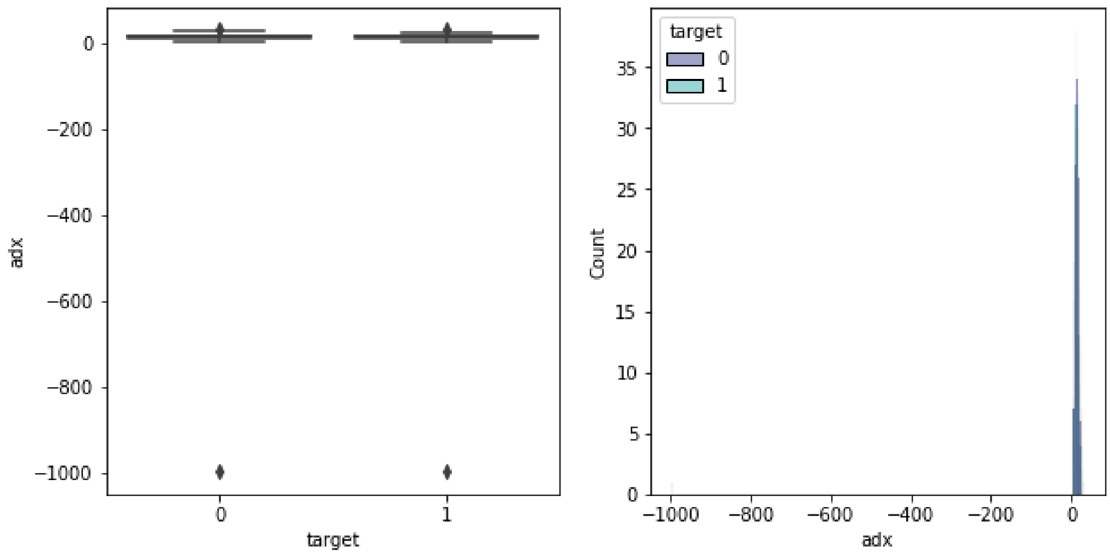

```
There is no significant difference in the distribution of Beta between
the True and False groups (p-value = 0.827)
```



There is a significant difference in the distribution of ATR between the True and False groups (p-value = 0.000)



There is no significant difference in the distribution of adx between the True and False groups (p-value = 0.962)




```
stats_good = (
              good_stocks
              .describe()
              .T
              .assign(skew = good_stocks.skew().tolist(),
                       kurt = good_stocks.kurtosis().tolist())
              .T
              )
stats_bad = (
              bad_stocks
              .describe()
              .T
              .assign(skew = bad_stocks.skew().tolist(),
                       kurt = bad_stocks.kurtosis().tolist())
              .T
              )

display(stats_good)
display(stats_bad)
```

```
       best_month  worst_month  total_yield  CompareToIndex
avg_Volume  \
count  246.000000   246.000000   246.000000       246.000000
2.460000e+02
mean    13.687687   -18.472048   -11.767191        -3.510241
5.327781e+06
std      6.766068     5.757157    14.841477        14.841477
9.419649e+06
min      1.112749   -45.096122   -50.898155       -42.641204
3.495257e+05
25%      9.430468   -21.089441   -21.605372       -13.348421
1.712501e+06
50%     12.600804   -17.893845   -10.574506        -2.317555
```

```
2.721312e+06
75%     15.916157   -14.323805    -1.954957         6.301994
4.641807e+06
max     53.404864    -5.503907    30.946239        39.203190
9.087958e+07
skew     2.347080    -1.412933    -0.102010        -0.102010
5.239098e+00
kurt     9.660260     3.893024    -0.061819        -0.061819
3.466932e+01

       percDaysOfProfit        sma10        sma30        sma50
RSI  \
count        246.000000   246.000000   246.000000   246.000000
246.000000
mean           0.483122   108.665386   108.745727   108.805653
48.620912
std            0.039611   172.195053   159.398049   148.217437
6.212578
min            0.384000     6.973777    10.996061    13.879911
30.875645
25%            0.456000    43.620889    48.141855    52.374417
44.021949
50%            0.480000    71.110542    73.407432    78.259535
49.515926
75%            0.512000   129.437950   130.491645   129.095262
53.293332
max            0.592000  2477.932736  2285.005408  2097.781820
62.277492
skew           0.190899    10.905966    10.667953    10.212162   -
0.299293
kurt          -0.203425   147.297572   142.731889   133.286836   -
0.627640

              std     bb_upper     bb_lower        Beta         ATR  \
count  246.000000   246.000000   246.000000  246.000000  246.000000
mean    12.148522   133.042770    84.448684    0.786300    3.685026
std      3.107711   158.979030   160.057511    0.089440    6.762633
min      8.888899    34.694049   -43.440962    0.403815    0.447716
25%     10.098875    75.301079    22.989845    0.724542    1.552212
50%     11.271043    97.810179    51.694371    0.782245    2.424696
75%     13.429298   153.867621   105.218759    0.841005    3.953616
max     32.130005  2306.396144  2263.614672    1.048238   97.793380
skew     2.509299    10.707911    10.578431   -0.022551   11.456287
kurt    10.262503   143.481217   141.124667    0.733272  155.120344

              adx  target
count  246.000000   246.0
mean    11.372631     1.0
std     64.839311     0.0
min   -999.000000     1.0
```

```
25%     12.177514     1.0
50%     14.975068     1.0
75%     18.149102     1.0
max     31.934611     1.0
skew   -15.569361     0.0
kurt   243.591299     0.0

       best_month  worst_month  total_yield  ComparedToIndex
avg_Volume  \
count  246.000000   246.000000   246.000000       246.000000
2.460000e+02
mean     6.803419    -9.666655    -4.027929         4.229022
5.286156e+06
std      4.142886     4.691953    13.865699        13.865699
8.933476e+06
min    -35.681820   -35.681820   -43.875399       -35.618448 -
9.990000e+02
25%      4.874897   -12.903153   -12.667127        -4.410176
1.864071e+06
50%      6.708873    -9.454481    -3.558029         4.698922
3.146631e+06
75%      8.906800    -6.177184     5.828578        14.085529
5.250518e+06
max     17.576911     0.028194    35.679781        43.936732
8.564579e+07
skew    -4.193270    -0.630349    -0.050561        -0.050561
6.476622e+00
kurt    44.320345     2.698183     0.137232         0.137232
4.923455e+01

       percDaysOfProfit        sma10        sma30        sma50
RSI  \
count        246.000000   246.000000   246.000000   246.000000
246.000000
mean           0.493518    96.725328    96.786889    96.782366
50.266468
std            0.059394   134.728288   125.532600   117.476352
7.196028
min            0.056000     9.676817    13.011460    12.990210
6.209353
25%            0.464000    44.983884    49.046520    52.882261
46.251575
50%            0.496000    71.980558    73.884079    74.076817
50.767306
75%            0.528000   105.091116   109.074253   108.525835
55.260566
max            0.616000  1852.319438  1733.245820  1611.587817
64.188848
skew          -2.446095     9.679007     9.657345     9.374449   -
1.088267
```

```
kurt          15.963621   120.027813   120.030519   114.775596
4.808992

              std     bb_upper     bb_lower        Beta         ATR  \
count  246.000000   246.000000   246.000000  246.000000  246.000000
mean     6.276076   109.339041    84.234737    0.788292    2.824793
std      1.849222   125.857972   125.315582    0.090728    4.091269
min      0.000000    23.823633    -2.084092    0.563835    0.303436
25%      5.038635    61.498910    36.139547    0.723459    1.346589
50%      6.686222    86.449289    60.996306    0.782995    2.028957
75%      7.706270   124.074125    95.386144    0.853049    2.983120
max      8.885942  1745.240398  1721.251242    1.035666   54.713205
skew    -0.684731     9.573440     9.716394    0.100729    9.174700
kurt    -0.305040   118.586010   121.067337   -0.267340  108.347534

              adx  target
count  246.000000   246.0
mean    11.352075     0.0
std     64.848817     0.0
min   -999.000000     0.0
25%     11.821135     0.0
50%     15.018912     0.0
75%     18.726280     0.0
max     31.731795     0.0
skew   -15.561517     0.0
kurt   243.426673     0.0
```

Testing the model

```
new_test['predicted_y'] = clf.predict(new_test.drop('stock',axis=1))

#correct for std feature, need to make sure it good for others

labelling_df['month_index'] = (labelling_df['t0'] / 30).astype(int)
label_months =
labelling_df.groupby(['stock','month_index']).apply(calculate_returns)
.reset_index()

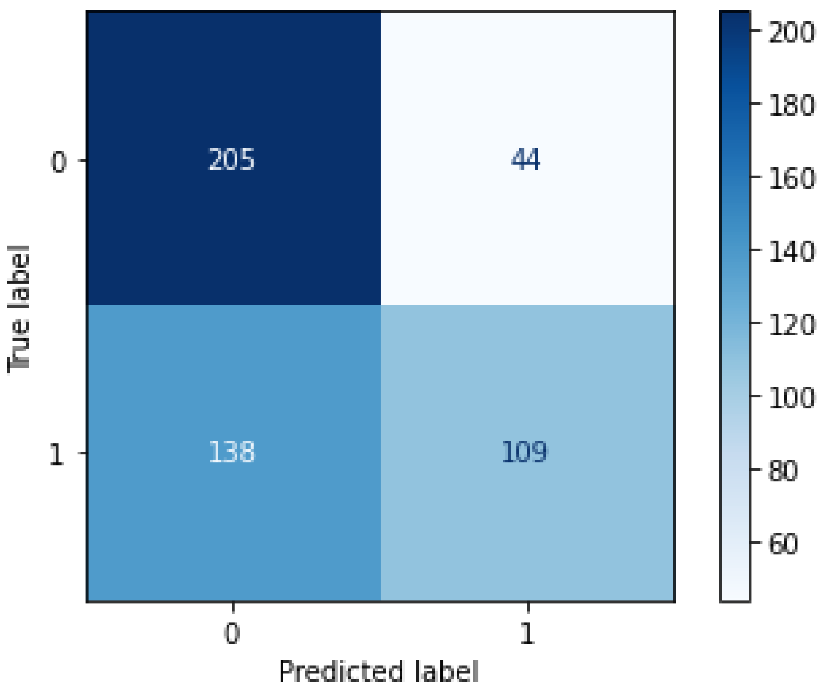
test_returns = label_months.groupby('stock')[0].std()
label_threshold = test_returns.median()

good_test = test_returns[test_returns > label_threshold].index

new_test = (
            new_test
            .assign(actual_y=np.where(new_test['stock'].isin(good_test
),1,0))
            )

Confusion_and_Report(new_test)
Get_ROC(new_test)
```

```
Train results:
  True positive: 109,
  True negative: 205,
  False positive: 44,
  False negative: 138
```

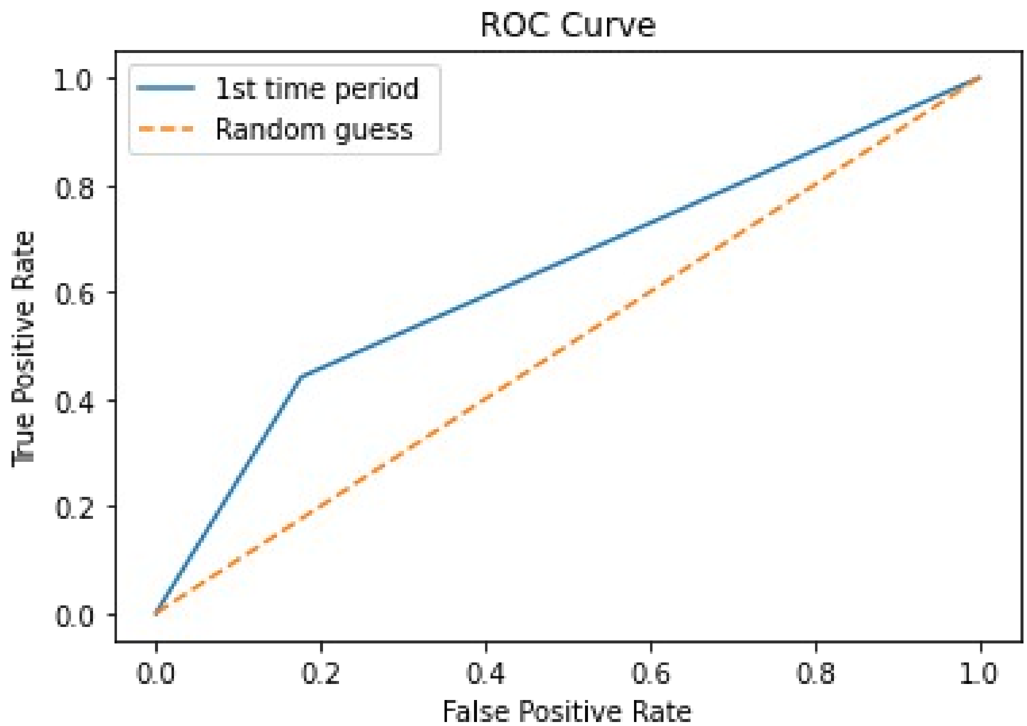



```
              precision    recall  f1-score   support

           0       0.60      0.82      0.69       249
           1       0.71      0.44      0.55       247

    accuracy                           0.63       496
   macro avg       0.66      0.63      0.62       496
weighted avg       0.65      0.63      0.62       496

0.6322943596247338
```



###1.3

```
predicted = reg.predict(np.array(reg_df[feature_chosen]).reshape(-
1,1))

df_using_pct_reg = (
                    new_train
                    .drop('target',axis=1)
                    .assign(pct_change_reg=predicted.tolist())
                    )

threshold = df_using_pct_reg['pct_change_reg'].median()

good = df_using_pct_reg.query('pct_change_reg > @threshold').index
bad = df_using_pct_reg.query('pct_change_reg < @threshold').index

df_using_pct_reg =
df_using_pct_reg.assign(target=np.where(df_using_pct_reg['pct_change_r
eg']>threshold,1,0))
```

Now we will do the stats analysis again

```
good_stocks = df_using_pct_reg[df_using_pct_reg['target'] == True]
bad_stocks = df_using_pct_reg[df_using_pct_reg['target'] == False]

from scipy.stats import mannwhitneyu
for feature in
df_using_pct_reg.drop(['stock','pct_change_reg','target'],axis=1).colu
```

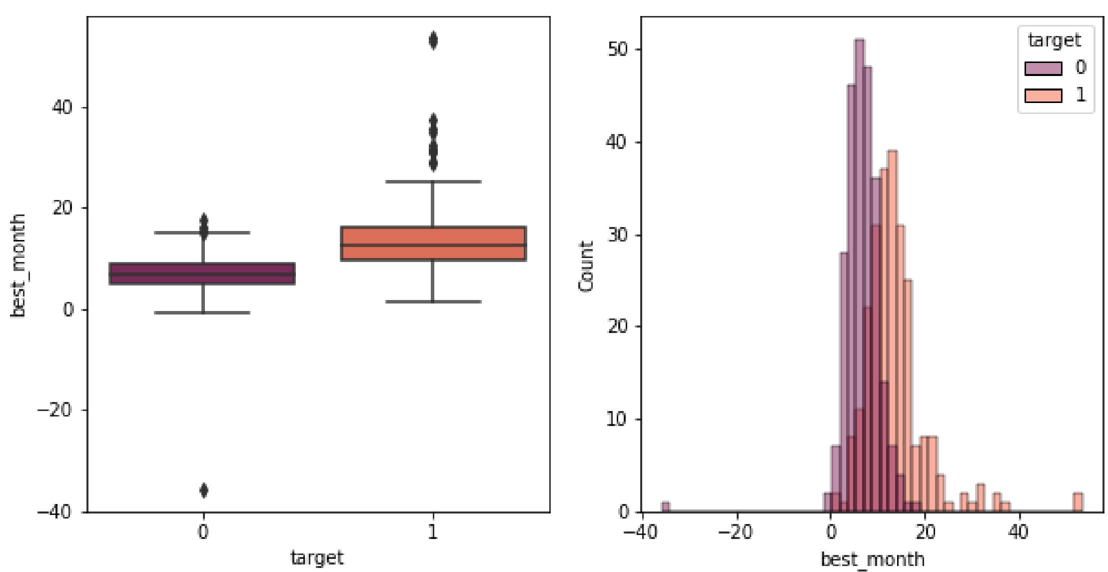
```
mns:
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))

    sns.boxplot(x='target', y=feature, data=df_using_pct_reg,
palette='rocket',ax=ax1)
    sns.histplot(x=feature,
data=df_using_pct_reg,palette='rocket',hue='target',ax=ax2)

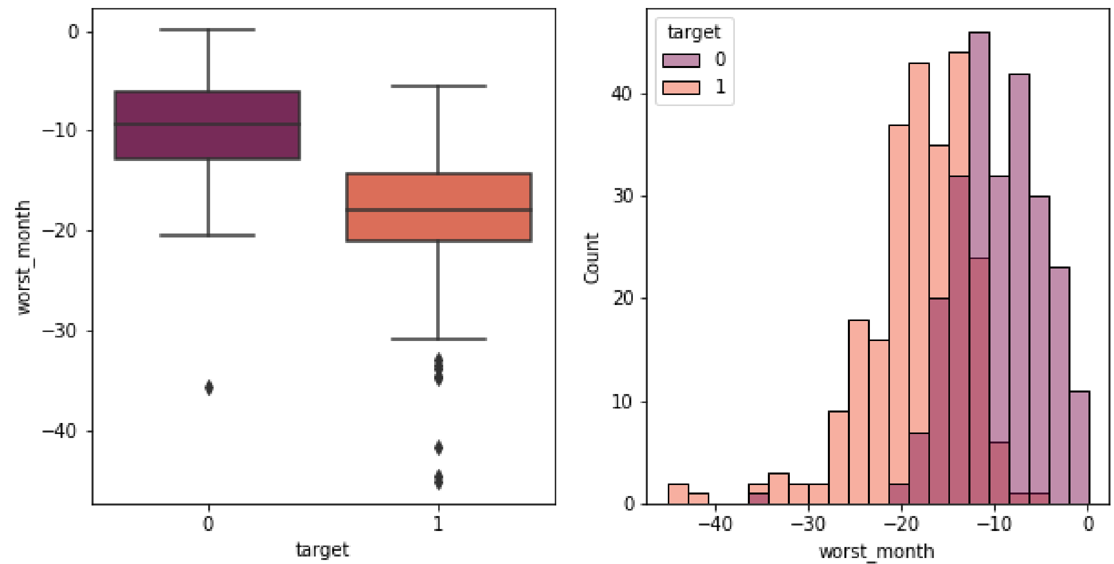
    statistic, pvalue = mannwhitneyu(good_stocks[feature],
bad_stocks[feature])
    if pvalue < 0.05:
        print(f'\033[1mThere is a significant difference in the
distribution of {feature} between the True and False groups (p-value =
{pvalue:.3f})\033[0m')
    else:
        print(f'\033[1mThere is no significant difference in the
distribution of {feature} between the True and False groups (p-value =
{pvalue:.3f})\033[0m')
    print()

    plt.show()
```

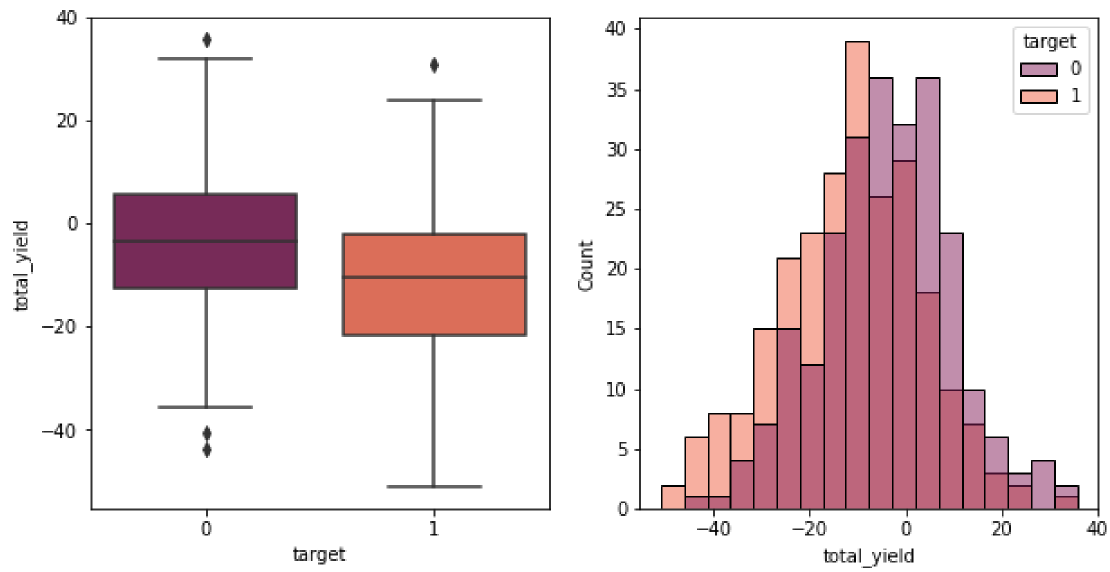
```
There is a significant difference in the distribution of best_month
between the True and False groups (p-value = 0.000)
```



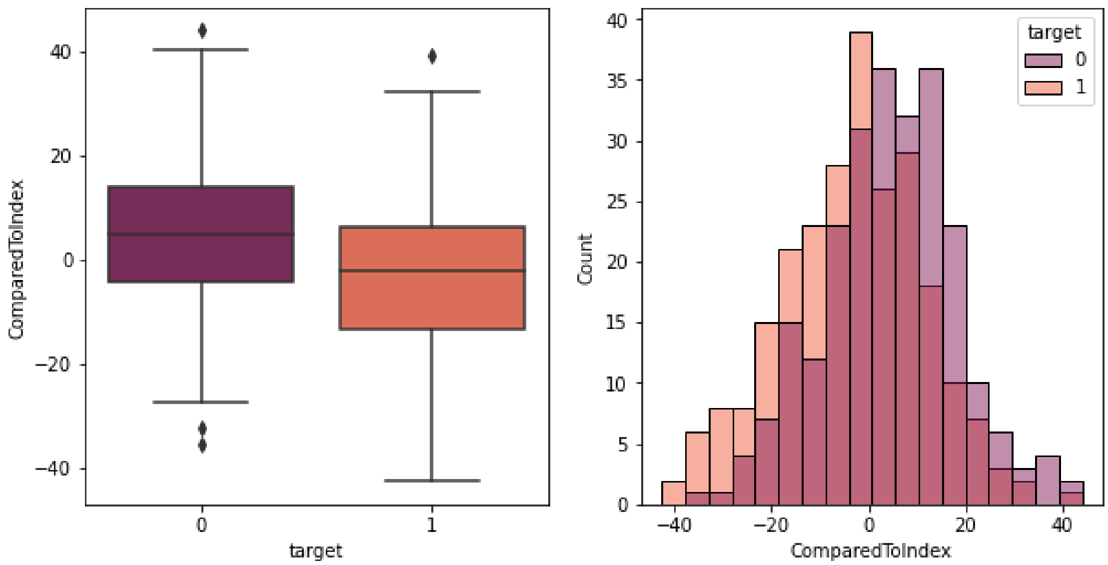

```
There is a significant difference in the distribution of worst_month
between the True and False groups (p-value = 0.000)
```



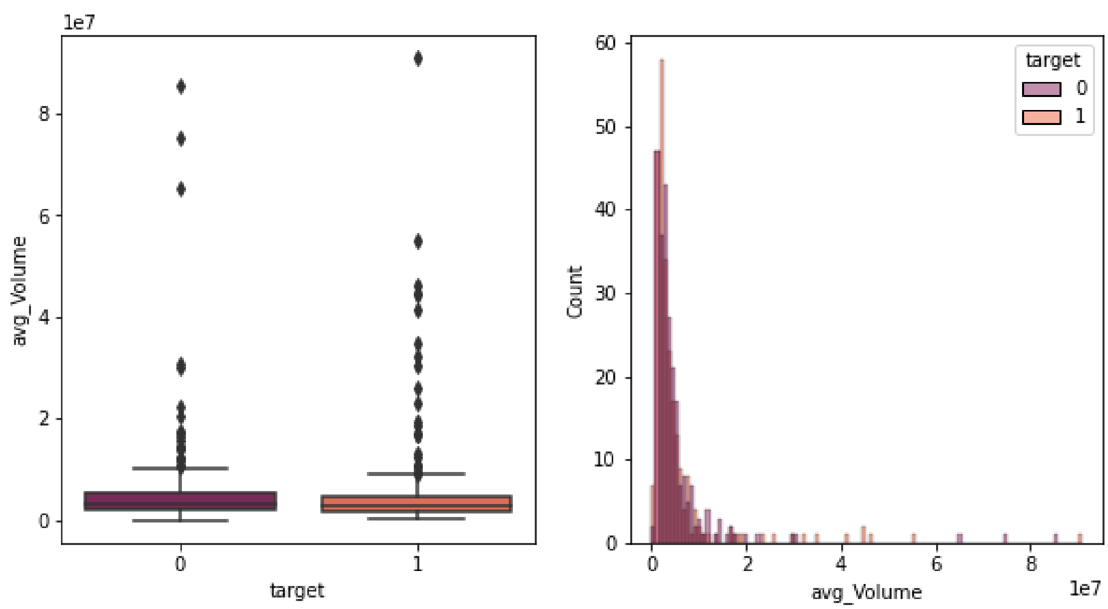

```
There is a significant difference in the distribution of total_yield
between the True and False groups (p-value = 0.000)
```



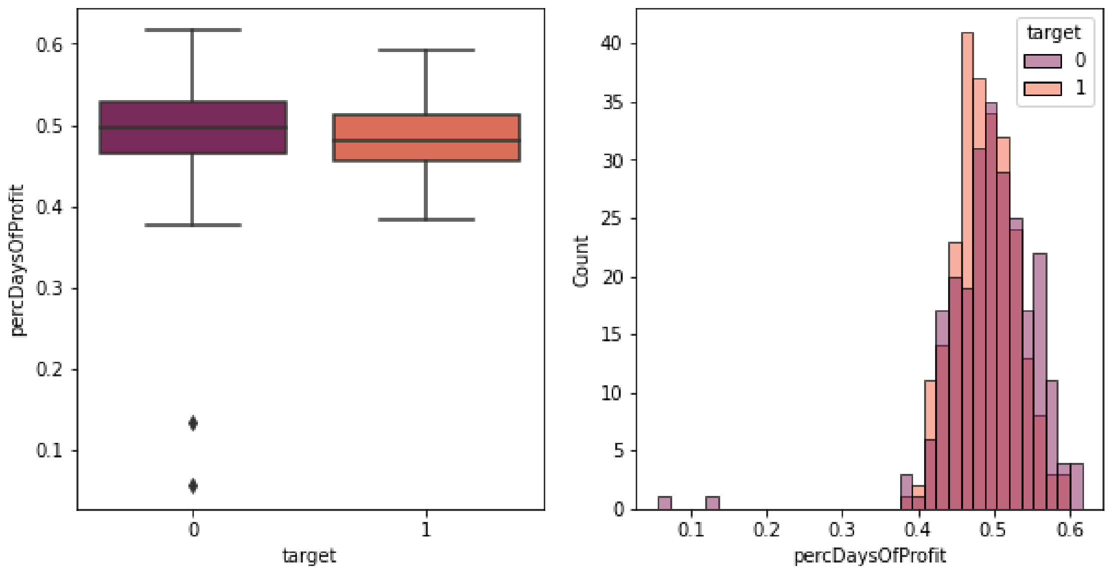

```
There is a significant difference in the distribution of
ComparedToIndex between the True and False groups (p-value = 0.000)
```



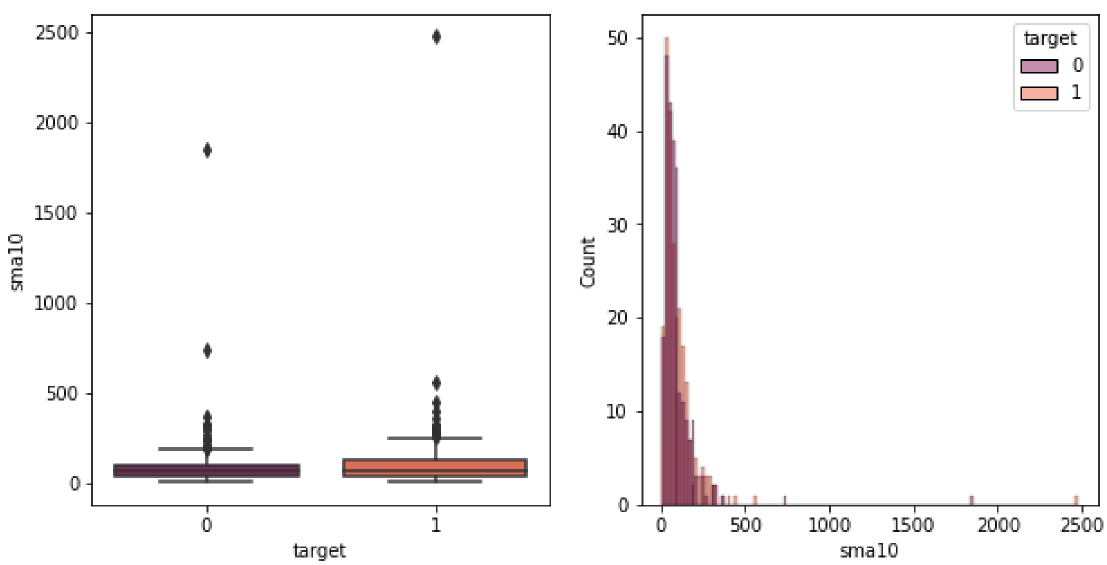
There is no significant difference in the distribution of avg_Volume between the True and False groups (p-value = 0.085)



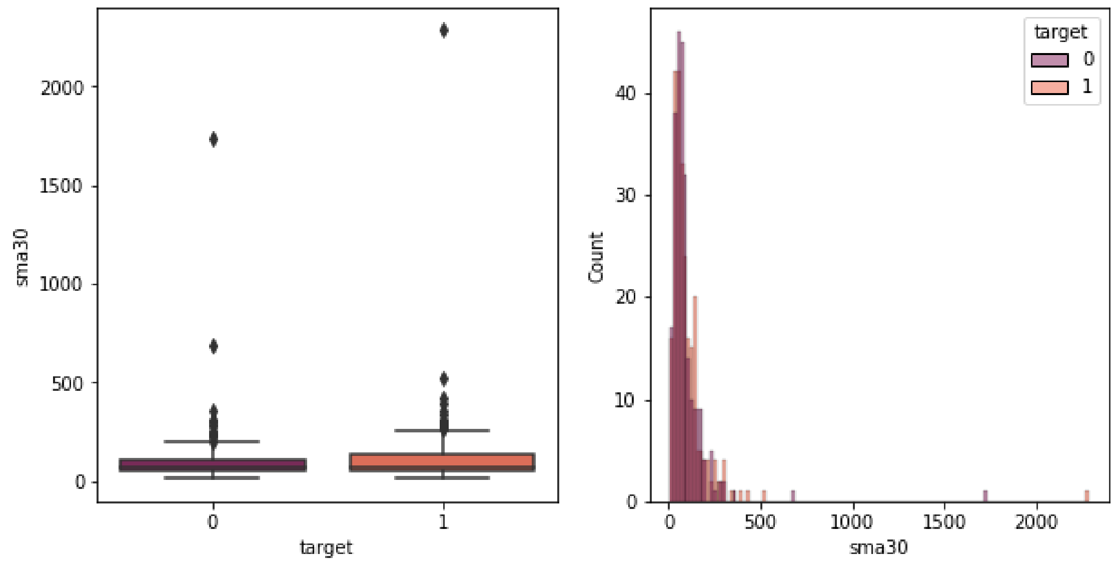
There is a significant difference in the distribution of percDaysOfProfit between the True and False groups (p-value = 0.002)



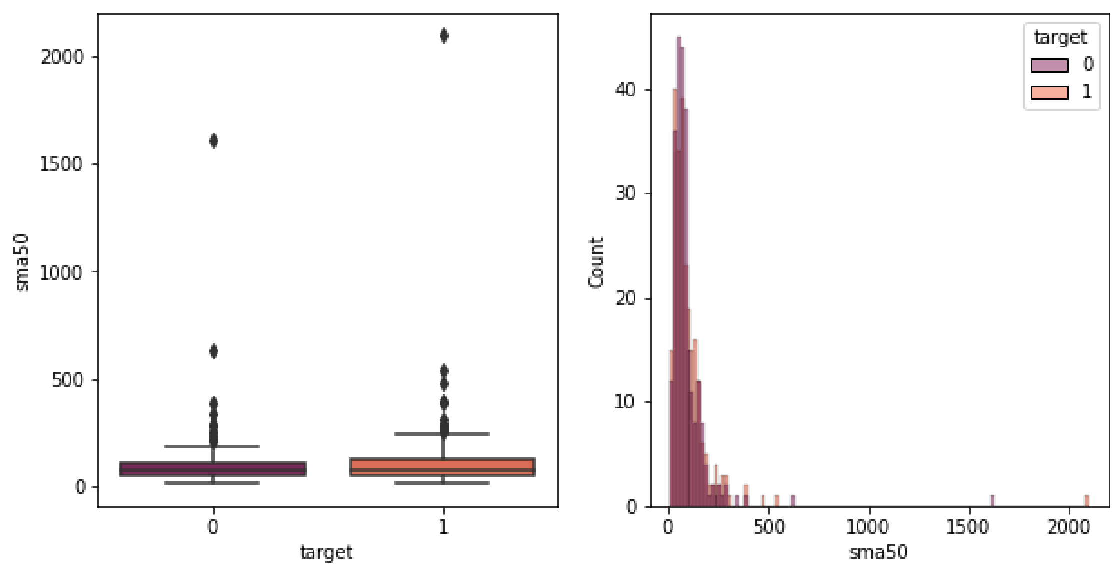

```
There is no significant difference in the distribution of sma10
between the True and False groups (p-value = 0.426)
```



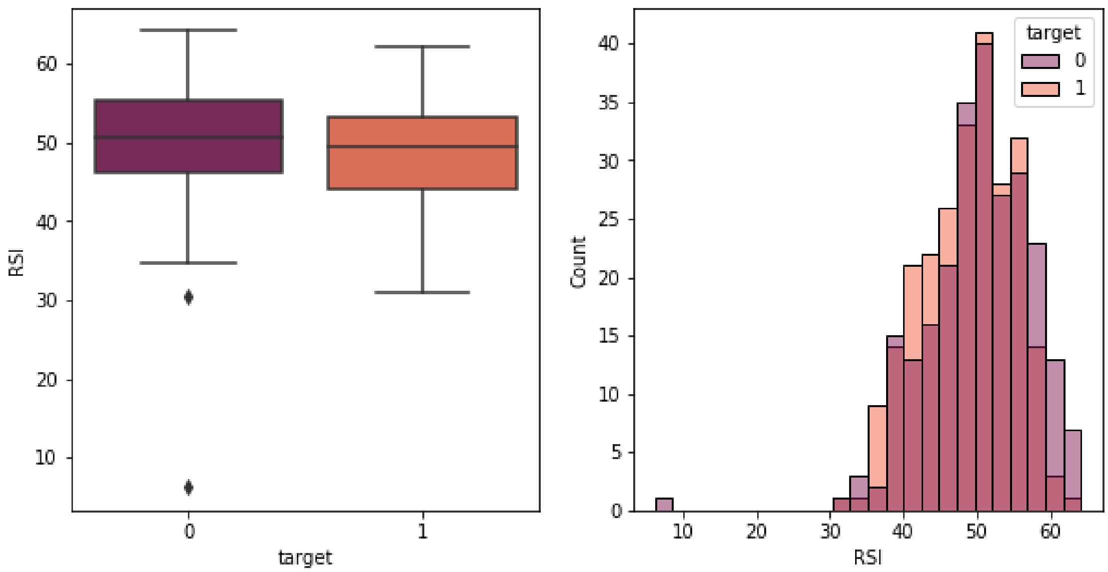

```
There is no significant difference in the distribution of sma30
between the True and False groups (p-value = 0.351)
```



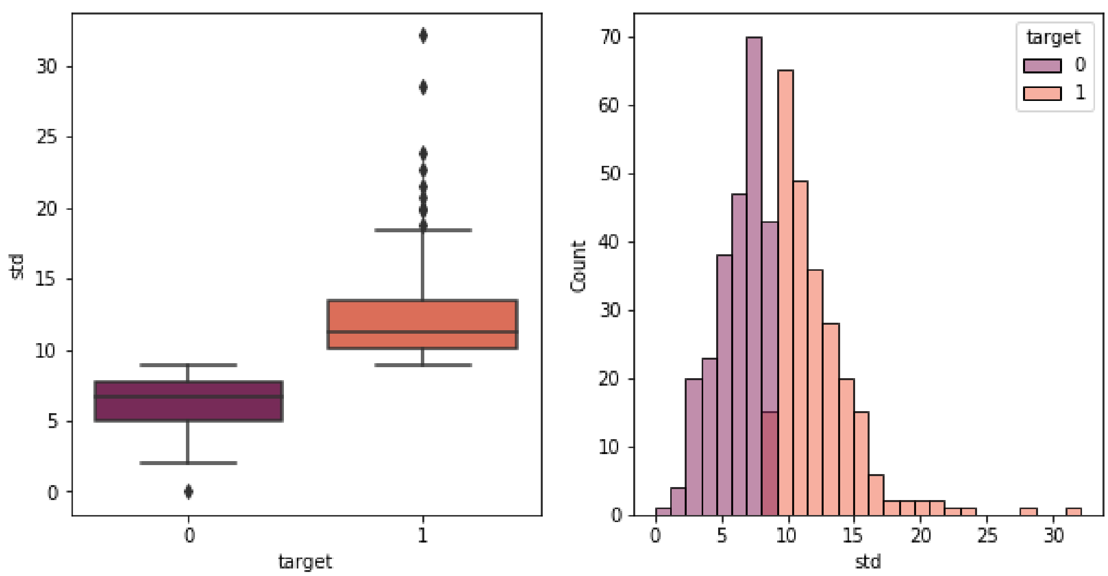
There is no significant difference in the distribution of sma50 between the True and False groups (p-value = 0.251)



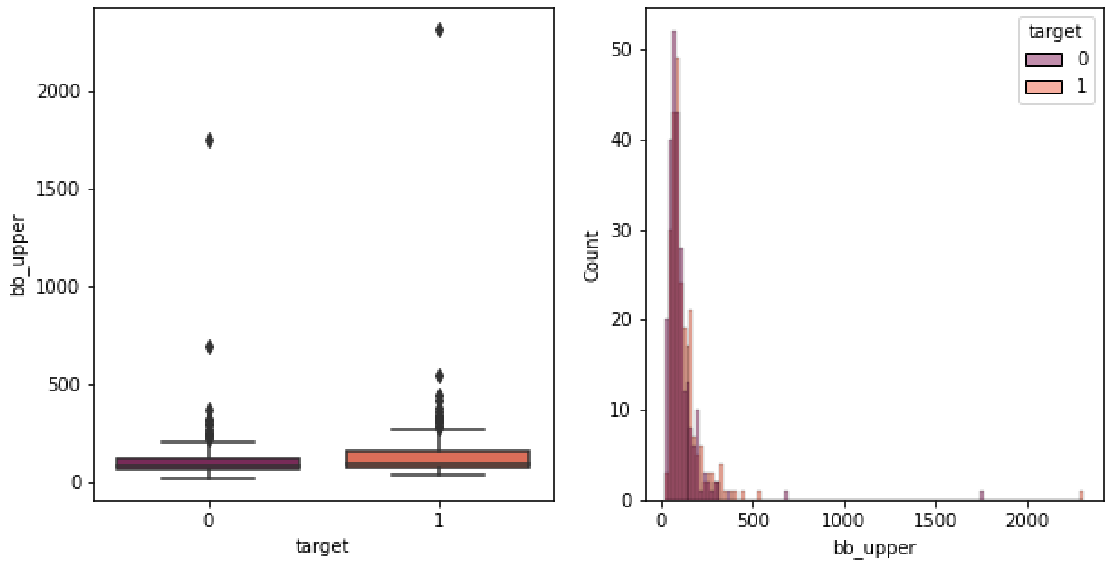
There is a significant difference in the distribution of RSI between the True and False groups (p-value = 0.004)



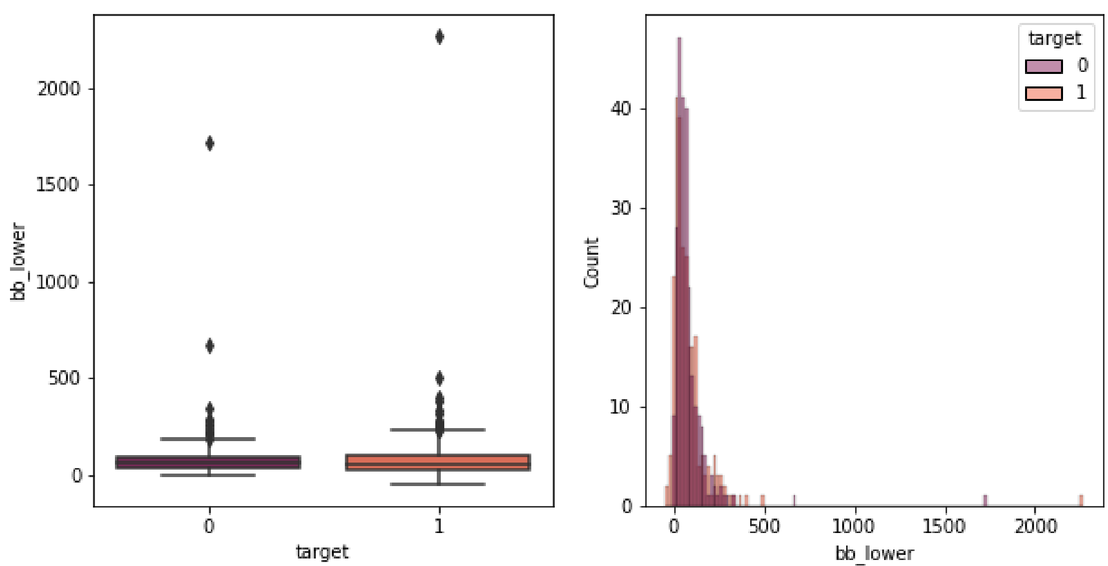
There is a significant difference in the distribution of std between the True and False groups (p-value = 0.000)



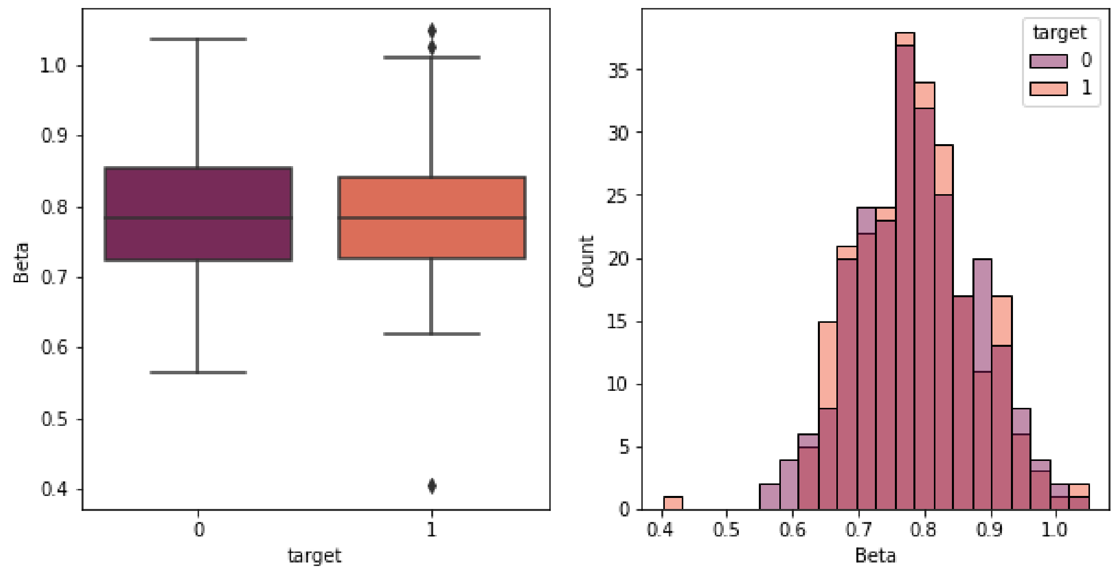
There is a significant difference in the distribution of bb_upper between the True and False groups (p-value = 0.000)



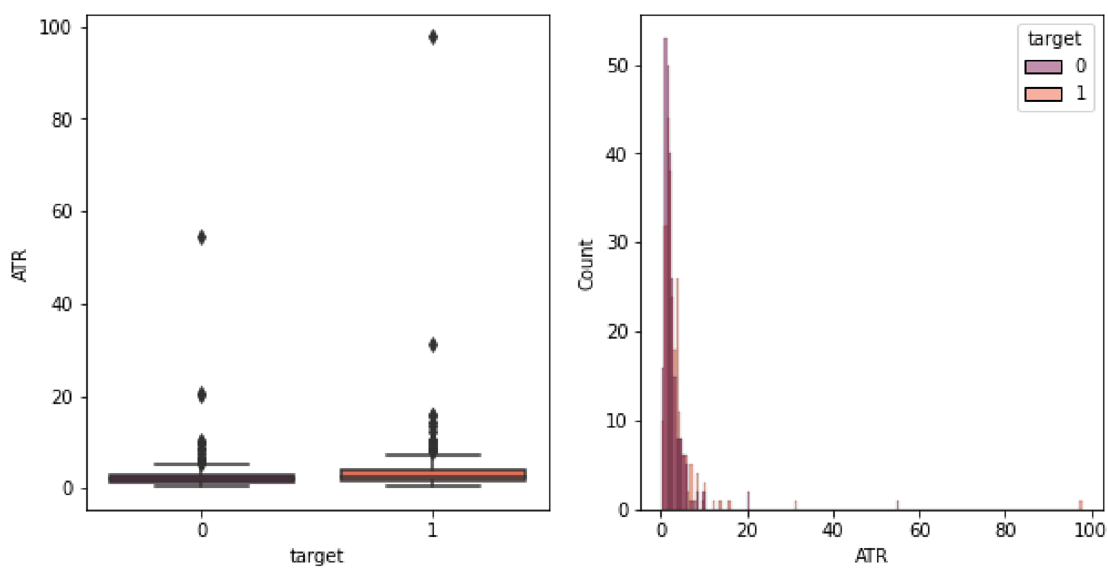

```
There is no significant difference in the distribution of bb_lower
between the True and False groups (p-value = 0.072)
```



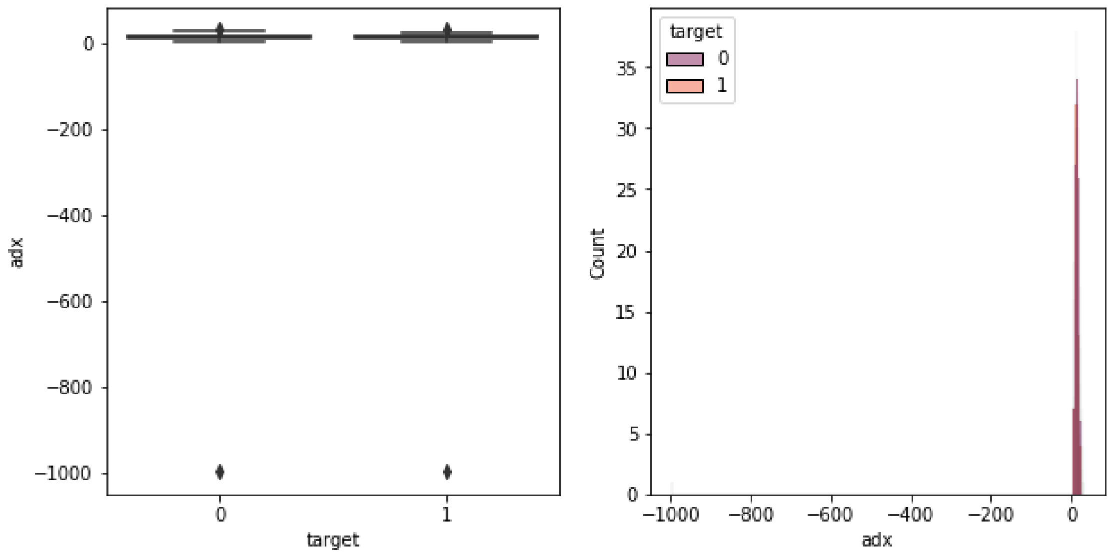

```
There is no significant difference in the distribution of Beta between
the True and False groups (p-value = 0.827)
```



There is a significant difference in the distribution of ATR between the True and False groups (p-value = 0.000)



There is no significant difference in the distribution of adx between the True and False groups (p-value = 0.962)




```
stats_good = (
              good_stocks
              .describe()
              .T
              .assign(skew = good_stocks.skew().tolist(),
                       kurt = good_stocks.kurtosis().tolist())
              .T
              )
stats_bad = (
              bad_stocks
             .describe()
              .T
              .assign(skew = bad_stocks.skew().tolist(),
                       kurt = bad_stocks.kurtosis().tolist())
              .T
              )

display(stats_good)
display(stats_bad)

       best_month  worst_month  total_yield  CompareToIndex
avg_Volume  \
count  246.000000   246.000000   246.000000       246.000000
2.460000e+02
mean    13.687687   -18.472048   -11.767191        -3.510241
5.327781e+06
std      6.766068     5.757157    14.841477        14.841477
9.419649e+06
min      1.112749   -45.096122   -50.898155       -42.641204
3.495257e+05
25%      9.430468   -21.089441   -21.605372       -13.348421
1.712501e+06
50%     12.600804   -17.893845   -10.574506        -2.317555
```

```
2.721312e+06
75%     15.916157   -14.323805    -1.954957         6.301994
4.641807e+06
max     53.404864    -5.503907    30.946239        39.203190
9.087958e+07
skew     2.347080    -1.412933    -0.102010        -0.102010
5.239098e+00
kurt     9.660260     3.893024    -0.061819        -0.061819
3.466932e+01

       percDaysOfProfit        sma10        sma30        sma50
RSI  \
count        246.000000   246.000000   246.000000   246.000000
246.000000
mean           0.483122   108.665386   108.745727   108.805653
48.620912
std            0.039611   172.195053   159.398049   148.217437
6.212578
min            0.384000     6.973777    10.996061    13.879911
30.875645
25%            0.456000    43.620889    48.141855    52.374417
44.021949
50%            0.480000    71.110542    73.407432    78.259535
49.515926
75%            0.512000   129.437950   130.491645   129.095262
53.293332
max            0.592000  2477.932736  2285.005408  2097.781820
62.277492
skew           0.190899    10.905966    10.667953    10.212162   -
0.299293
kurt          -0.203425   147.297572   142.731889   133.286836   -
0.627640

              std     bb_upper     bb_lower         Beta         ATR  \
count  246.000000   246.000000   246.000000   246.000000  246.000000
mean    12.148522   133.042770    84.448684     0.786300    3.685026
std      3.107711   158.979030   160.057511     0.089440    6.762633
min      8.888899    34.694049   -43.440962     0.403815    0.447716
25%     10.098875    75.301079    22.989845     0.724542    1.552212
50%     11.271043    97.810179    51.694371     0.782245    2.424696
75%     13.429298   153.867621   105.218759     0.841005    3.953616
max     32.130005  2306.396144  2263.614672     1.048238   97.793380
skew     2.509299    10.707911    10.578431    -0.022551   11.456287
kurt    10.262503   143.481217   141.124667     0.733272  155.120344

              adx  pct_change_reg  target
count  246.000000      246.000000   246.0
mean    11.372631       17.790088     1.0
std     64.839311        1.631534     0.0
min   -999.000000       16.078802     1.0
```

```
25%     12.177514       16.714033     1.0
50%     14.975068       17.329416     1.0
75%     18.149102       18.462489     1.0
max     31.934611       28.280271     1.0
skew   -15.569361        2.509299     0.0
kurt   243.591299       10.262503     0.0

       best_month  worst_month  total_yield  ComparedToIndex
avg_Volume  \
count  246.000000   246.000000   246.000000       246.000000
2.460000e+02
mean     6.803419    -9.666655    -4.027929         4.229022
5.286156e+06
std      4.142886     4.691953    13.865699        13.865699
8.933476e+06
min    -35.681820   -35.681820   -43.875399       -35.618448 -
9.990000e+02
25%      4.874897   -12.903153   -12.667127        -4.410176
1.864071e+06
50%      6.708873    -9.454481    -3.558029         4.698922
3.146631e+06
75%      8.906800    -6.177184     5.828578        14.085529
5.250518e+06
max     17.576911     0.028194    35.679781        43.936732
8.564579e+07
skew    -4.193270    -0.630349    -0.050561        -0.050561
6.476622e+00
kurt    44.320345     2.698183     0.137232         0.137232
4.923455e+01

       percDaysOfProfit        sma10        sma30        sma50
RSI  \
count        246.000000   246.000000   246.000000   246.000000
246.000000
mean           0.493518    96.725328    96.786889    96.782366
50.266468
std            0.059394   134.728288   125.532600   117.476352
7.196028
min            0.056000     9.676817    13.011460    12.990210
6.209353
25%            0.464000    44.983884    49.046520    52.882261
46.251575
50%            0.496000    71.980558    73.884079    74.076817
50.767306
75%            0.528000   105.091116   109.074253   108.525835
55.260566
max            0.616000  1852.319438  1733.245820  1611.587817
64.188848
skew          -2.446095     9.679007     9.657345     9.374449   -
1.088267
```

```
kurt          15.963621   120.027813   120.030519   114.775596
4.808992

              std     bb_upper     bb_lower        Beta         ATR  \
count  246.000000   246.000000   246.000000  246.000000  246.000000
mean     6.276076   109.339041    84.234737    0.788292    2.824793
std      1.849222   125.857972   125.315582    0.090728    4.091269
min      0.000000    23.823633    -2.084092    0.563835    0.303436
25%      5.038635    61.498910    36.139547    0.723459    1.346589
50%      6.686222    86.449289    60.996306    0.782995    2.028957
75%      7.706270   124.074125    95.386144    0.853049    2.983120
max      8.885942  1745.240398  1721.251242    1.035666   54.713205
skew    -0.684731     9.573440     9.716394    0.100729    9.174700
kurt    -0.305040   118.586010   121.067337   -0.267340  108.347534

              adx  pct_change_reg  target
count  246.000000      246.000000   246.0
mean    11.352075       14.707082     0.0
std     64.848817        0.970833     0.0
min   -999.000000       11.412172     0.0
25%     11.821135       14.057431     0.0
50%     15.018912       14.922407     0.0
75%     18.726280       15.457927     0.0
max     31.731795       16.077249     0.0
skew   -15.561517       -0.684731     0.0
kurt   243.426673       -0.305040     0.0
```

####Testing using the regression values

```
threshold = df_using_pct_reg['pct_change_reg'].median()

good = (
        df_using_pct_reg
        .set_index('stock')
        .query('pct_change_reg > @threshold')
        .index)

bad = (
        df_using_pct_reg
        .set_index('stock')
        .query('pct_change_reg < @threshold')
        .index)

train_reg = (
            df_using_pct_reg
            .assign(target=np.where(df_using_pct_reg['stock'].isin(goo
d),1,0))
            )
```

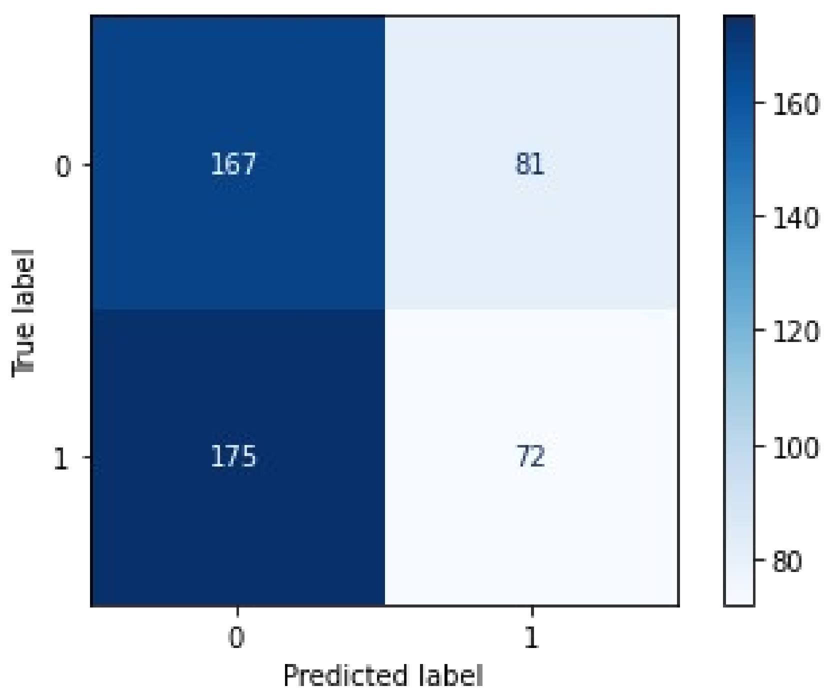
```
clf = RandomForestClassifier(max_depth=3, random_state=0)
clf.fit(train_reg.drop(['stock','pct_change_reg','target'],axis=1),
train_reg['target'])
reg_test = new_test.drop(['predicted_y','actual_y'],axis=1).copy()
reg_test['predicted_y'] = clf.predict(reg_test.drop('stock',axis=1))

label_df = (
            add_label_to_labelling_df(labelling_df)
            .reset_index()
            .drop('pct_price_movement',axis=1)
            )

reg_test = pd.merge(reg_test, label_df, on =
'stock',how='inner').rename(columns={'label':'actual_y'})

Confusion_and_Report(reg_test)
Get_ROC(reg_test)
```

```
        Train results:
          True positive: 72,
          True negative: 167,
          False positive: 81,
          False negative: 175
```

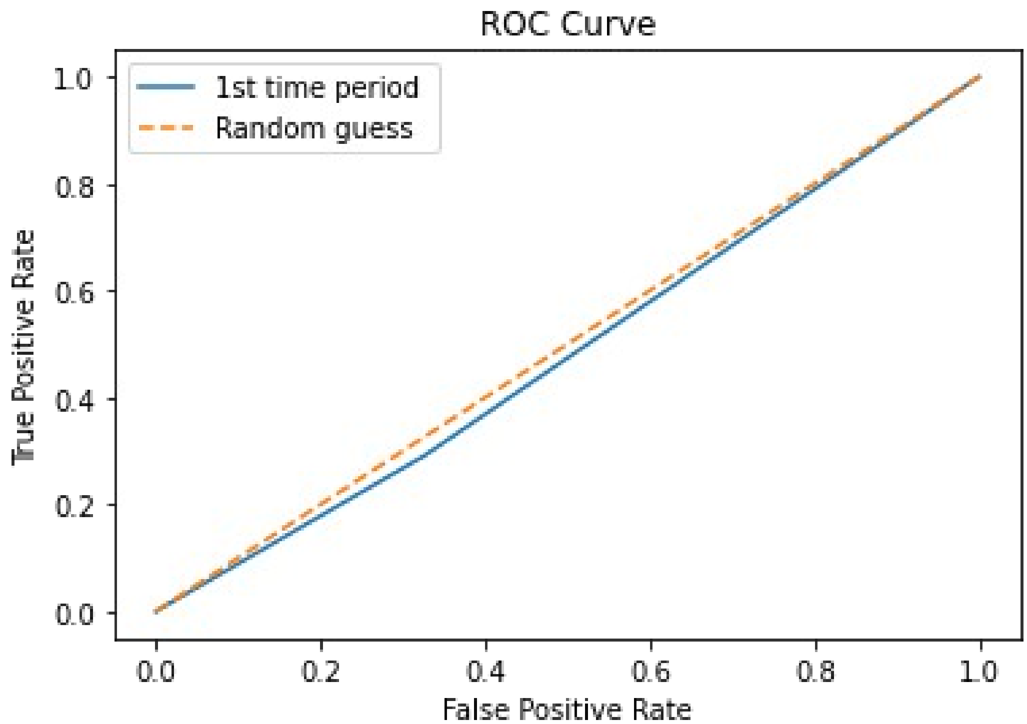


```
              precision    recall  f1-score   support

       False       0.49      0.67      0.57       248
        True       0.47      0.29      0.36       247

    accuracy                           0.48       495
   macro avg       0.48      0.48      0.46       495
weighted avg       0.48      0.48      0.46       495

0.4824425362413478
```



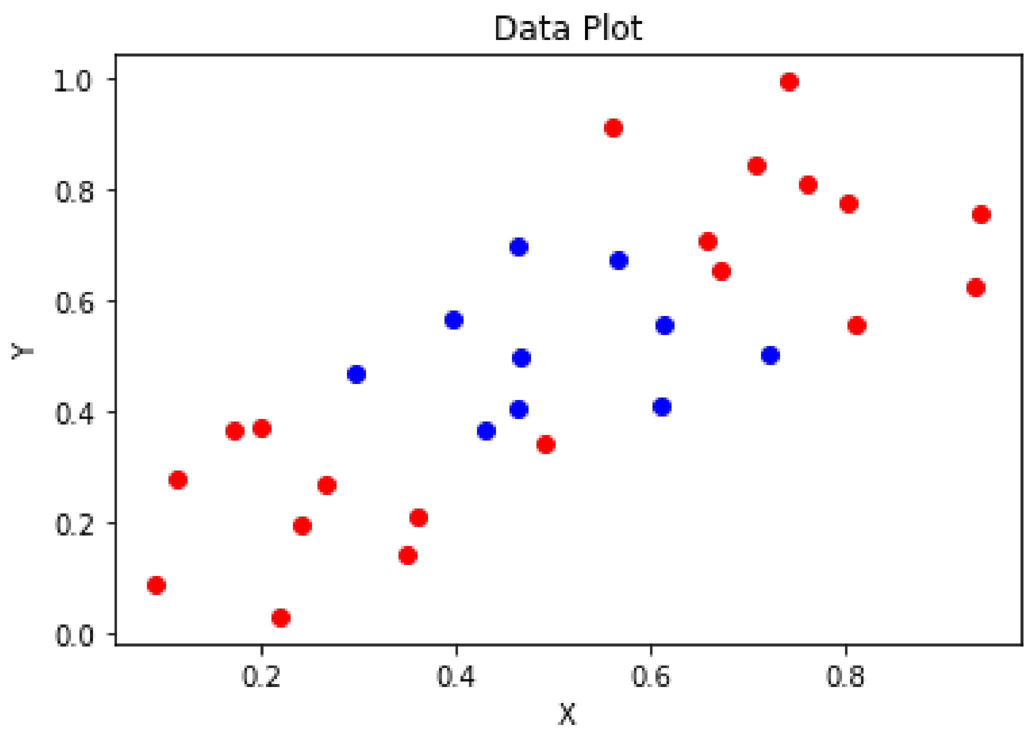
###1.4

At first we tried to pick a feature which will enable us to find a plane where the two groups(good stocks/bad stocks) are easily seperated by a linear line, our closest feature to do so was the std of monthly revenue, even then it wasnt a good enough seperator for a couple of reasons, firstly there isnt any one 'simple' feature that can do so in the stocks domain due to its complexity nature, secondly we used a linear regressor which is limited in its nature, even if we found a good enough feature that was able transform the plane so its easy to seperate the two groups it doesnt mean that a linear line could do so(refer to example A).

linear regression by itself isnt a strong enough model for predicting good or bad stocks but it can be used as a tool for feature creations of trend based features

```
#@title example A
np.random.seed(123)
```

```python
low_data = np.random.rand(10, 2) * 0.5
mid_data = np.random.rand(10, 2) * 0.5 + 0.25
high_data = np.random.rand(10, 2) * 0.5 + 0.5

# Create the plot and scatter the data
fig, ax = plt.subplots()
ax.scatter(low_data[:, 0], low_data[:, 1], color='red')
ax.scatter(mid_data[:, 0], mid_data[:, 1], color='blue')
ax.scatter(high_data[:, 0], high_data[:, 1], color='red')

# Add labels and titles
ax.set_xlabel('X')
ax.set_ylabel('Y')
ax.set_title('Data Plot')

# Show the plot
plt.show()
```



So to sum up we tried to predict the stocks that will have high performance in the next 3 months. obviously we saw that the linear regression not predicting well by herself , i mean that the value of our feature not predicting well by linear regression the value of the change. but it can indicate a trend, so when we chose threshold we saw that the feature values can predict not bad in general which stocks are better.

##Second Assignment

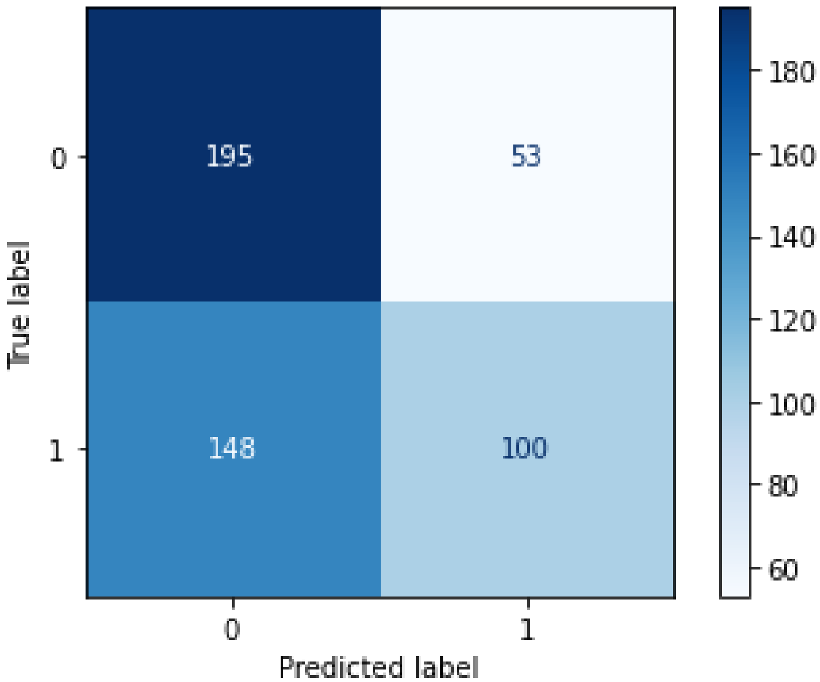
####2.1

the training df was done in the first part of this notebook has it was used for previous assignment

###2.2 - Testing 12 times

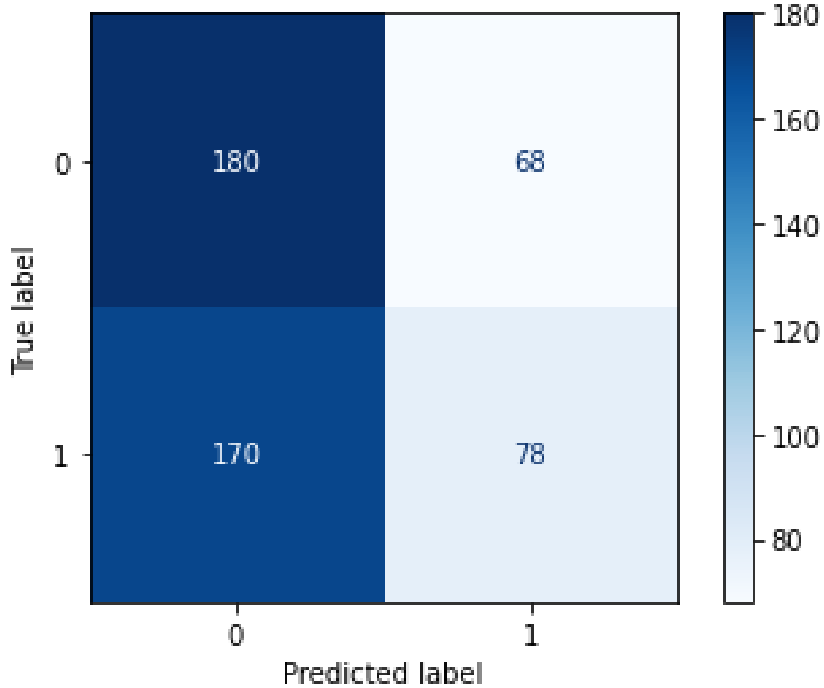
```
for i in range(0,12):
  print(f'test iteration = {i+1}')
  all_features_test_df,all_labelling_test_df =
get_features_labels_from_full_dataframe(all_df,start_train_features_da
y = 270+30*i)
  features_df2 = all_features_test_df.copy()
  monthly_features_df2 = Get_Monthly(all_features_test_df)

  test_df = (
            calculate_featurs(all_features_test_df)
            .reset_index()
            .pipe(lambda d:Get_all_features(d, features_df2,
monthly_features_df2))
            .assign(predicted_y = lambda
d:clf.predict(d.drop('stock',axis=1)))
            .pipe(lambda d:add_actual(d,all_labelling_test_df))
            )
  Confusion_and_Report(test_df)
```

```
test iteration = 1
start_date:270 , end_ft_day: 450        start_lbl_date:451 ,
end_lbl_day: 541

        Train results:
          True positive: 100,
          True negative: 195,
          False positive: 53,
          False negative: 148
```

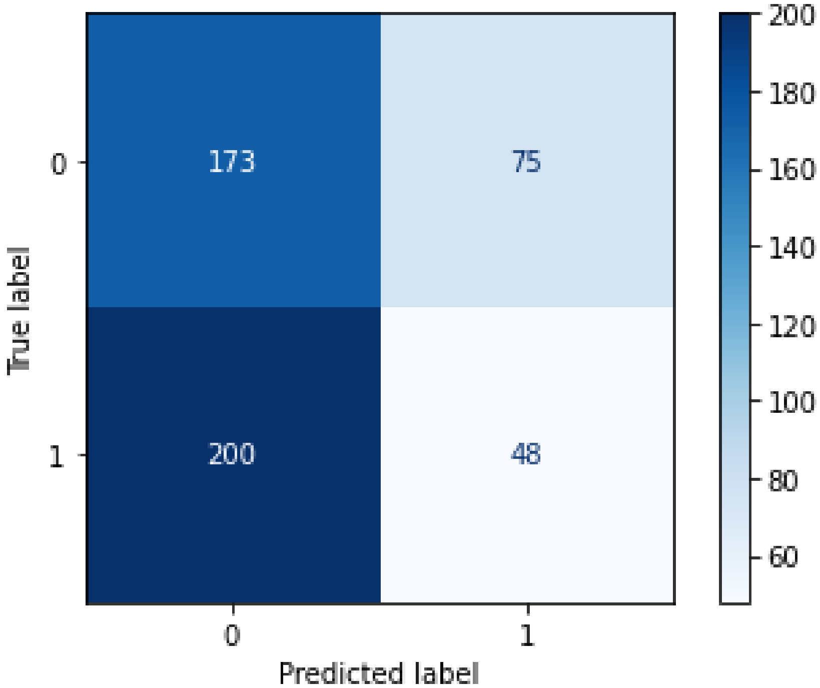


	precision	recall	f1-score	support
0.0	0.57	0.79	0.66	248
1.0	0.65	0.40	0.50	248
accuracy			0.59	496
macro avg	0.61	0.59	0.58	496
weighted avg	0.61	0.59	0.58	496

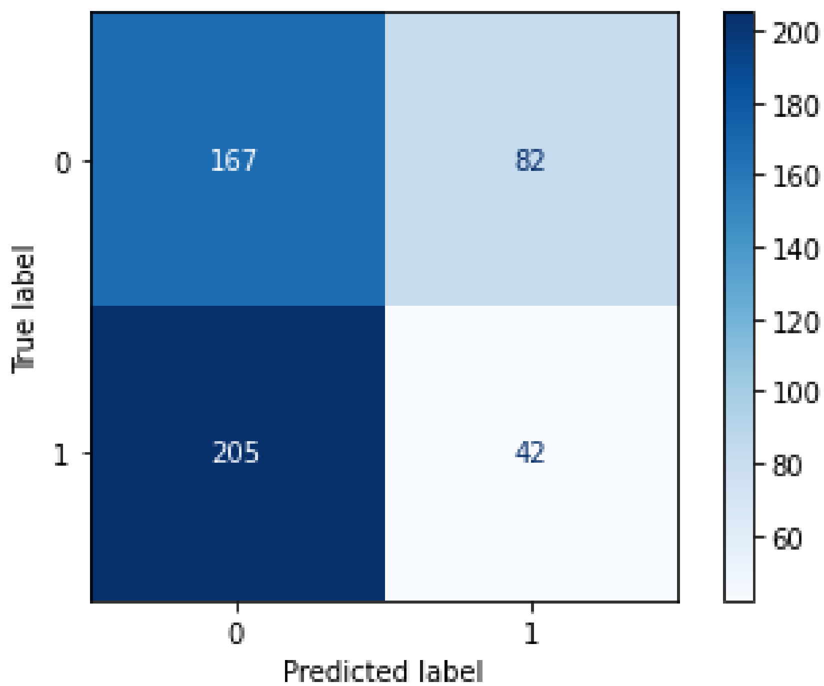
```
test iteration = 2
start_date:300 , end_ft_day: 480        start_lbl_date:481 ,
end_lbl_day: 571

        Train results:
          True positive: 78,
          True negative: 180,
          False positive: 68,
          False negative: 170
```



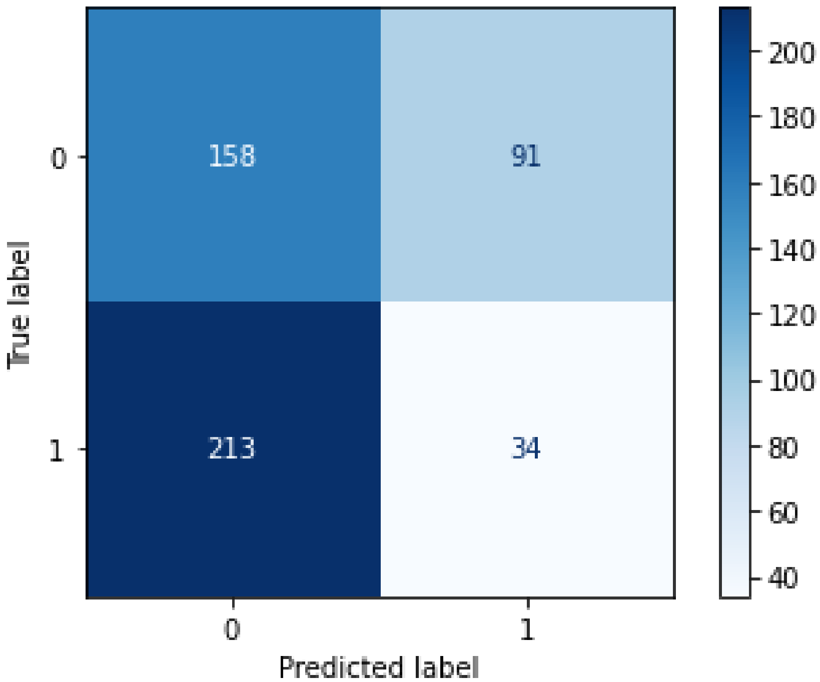

```
              precision    recall  f1-score   support

         0.0       0.51      0.73      0.60       248
         1.0       0.53      0.31      0.40       248

    accuracy                           0.52       496
   macro avg       0.52      0.52      0.50       496
weighted avg       0.52      0.52      0.50       496

test iteration = 3
start_date:330 , end_ft_day: 510        start_lbl_date:511 ,
end_lbl_day: 601

        Train results:
          True positive: 48,
          True negative: 173,
          False positive: 75,
          False negative: 200
```



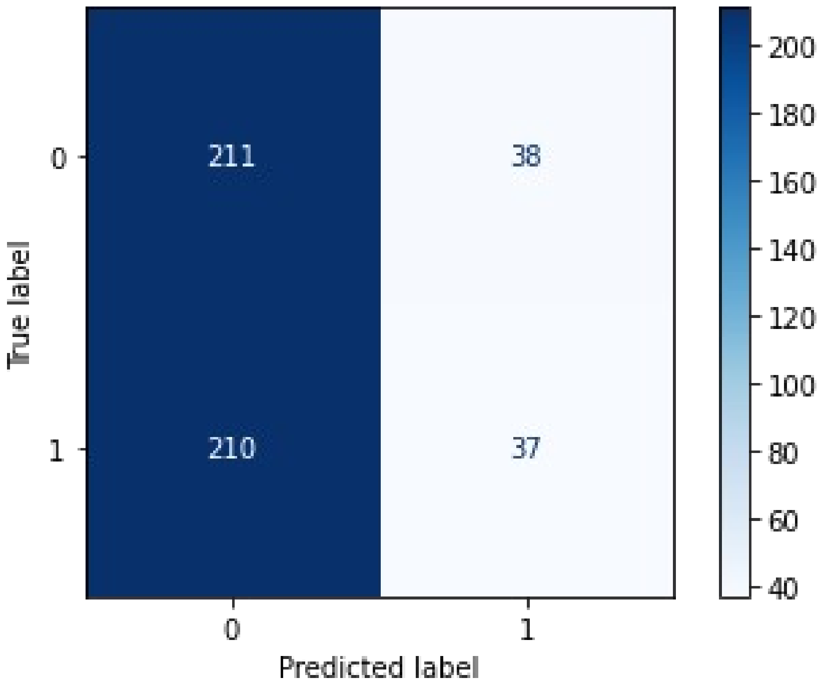

```
              precision    recall  f1-score   support

         0.0       0.46      0.70      0.56       248
         1.0       0.39      0.19      0.26       248

    accuracy                           0.45       496
   macro avg       0.43      0.45      0.41       496
weighted avg       0.43      0.45      0.41       496

test iteration = 4
start_date:360 , end_ft_day: 540        start_lbl_date:541 ,
end_lbl_day: 631

        Train results:
          True positive: 42,
          True negative: 167,
          False positive: 82,
          False negative: 205
```




```
              precision    recall  f1-score   support

         0.0       0.45      0.67      0.54       249
         1.0       0.34      0.17      0.23       247

    accuracy                           0.42       496
   macro avg       0.39      0.42      0.38       496
weighted avg       0.39      0.42      0.38       496

test iteration = 5
start_date:390 , end_ft_day: 570        start_lbl_date:571 ,
end_lbl_day: 661

        Train results:
          True positive: 34,
          True negative: 158,
          False positive: 91,
          False negative: 213
```

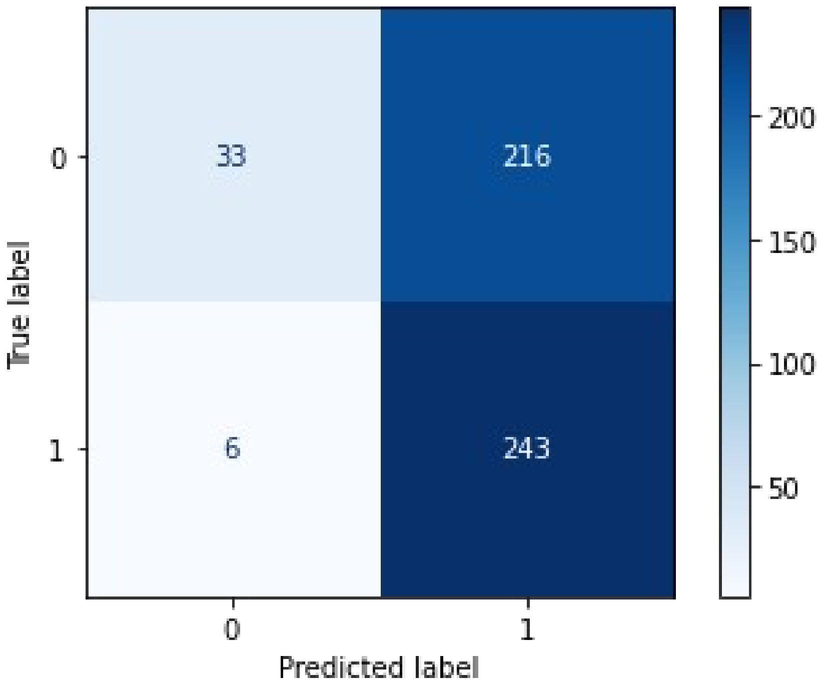



```
              precision    recall  f1-score   support

         0.0       0.43      0.63      0.51       249
         1.0       0.27      0.14      0.18       247

    accuracy                           0.39       496
   macro avg       0.35      0.39      0.35       496
weighted avg       0.35      0.39      0.35       496

test iteration = 6
start_date:420 , end_ft_day: 600        start_lbl_date:601 ,
end_lbl_day: 691

        Train results:
          True positive: 37,
          True negative: 211,
          False positive: 38,
          False negative: 210
```

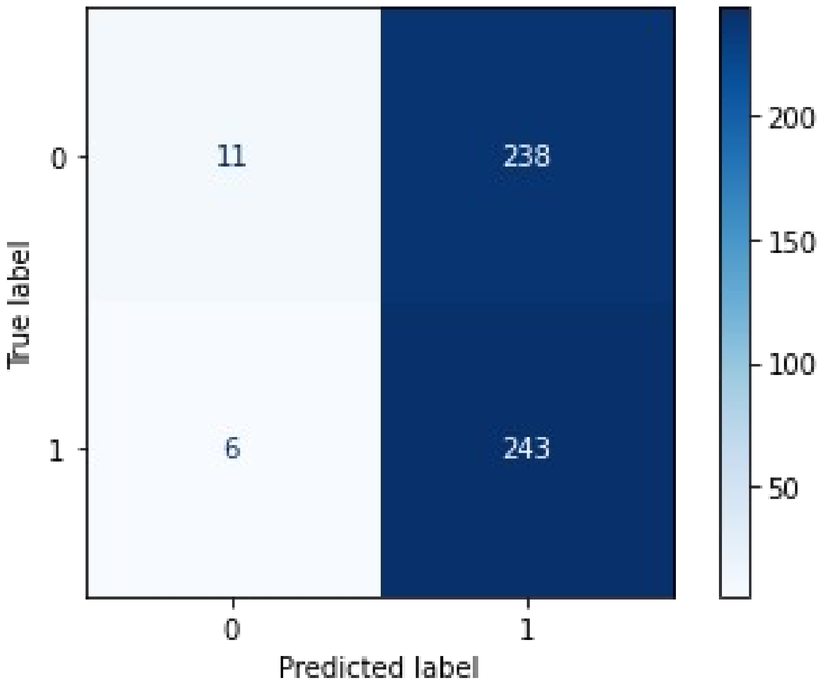


	precision	recall	f1-score	support
0.0	0.50	0.85	0.63	249
1.0	0.49	0.15	0.23	247
accuracy			0.50	496
macro avg	0.50	0.50	0.43	496
weighted avg	0.50	0.50	0.43	496

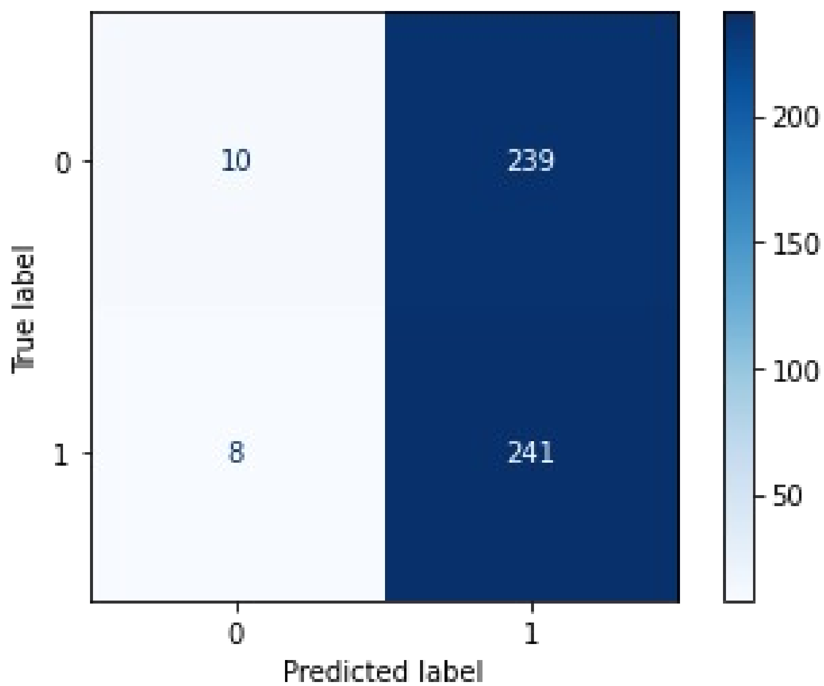
```
test iteration = 7
start_date:450 , end_ft_day: 630        start_lbl_date:631 ,
end_lbl_day: 721

        Train results:
          True positive: 243,
          True negative: 33,
          False positive: 216,
          False negative: 6
```



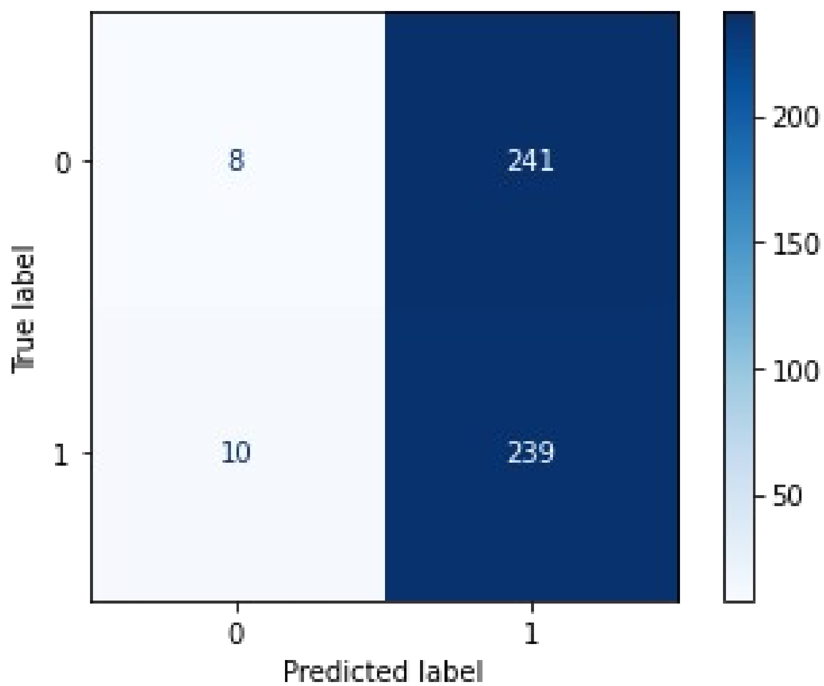

```
              precision    recall  f1-score   support

         0.0       0.85      0.13      0.23       249
         1.0       0.53      0.98      0.69       249

    accuracy                           0.55       498
   macro avg       0.69      0.55      0.46       498
weighted avg       0.69      0.55      0.46       498

test iteration = 8
start_date:480 , end_ft_day: 660        start_lbl_date:661 ,
end_lbl_day: 751

        Train results:
          True positive: 243,
          True negative: 11,
          False positive: 238,
          False negative: 6
```



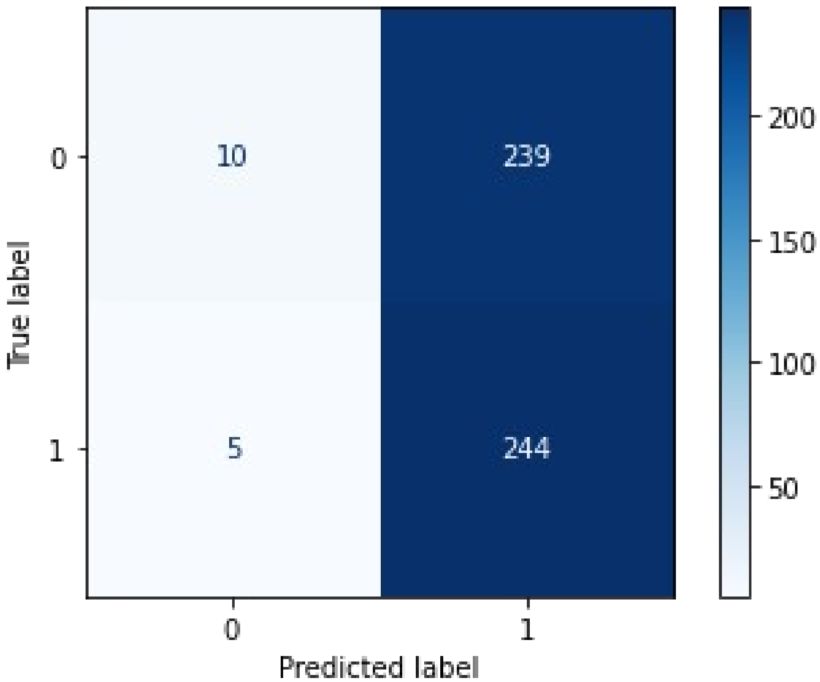

```
              precision    recall  f1-score   support

         0.0       0.65      0.04      0.08       249
         1.0       0.51      0.98      0.67       249

    accuracy                           0.51       498
   macro avg       0.58      0.51      0.37       498
weighted avg       0.58      0.51      0.37       498

test iteration = 9
start_date:510 , end_ft_day: 690        start_lbl_date:691 ,
end_lbl_day: 781

        Train results:
          True positive: 241,
          True negative: 10,
          False positive: 239,
          False negative: 8
```




```
              precision    recall  f1-score   support

         0.0       0.56      0.04      0.07       249
         1.0       0.50      0.97      0.66       249

    accuracy                           0.50       498
   macro avg       0.53      0.50      0.37       498
weighted avg       0.53      0.50      0.37       498

test iteration = 10
start_date:540 , end_ft_day: 720        start_lbl_date:721 ,
end_lbl_day: 811

        Train results:
          True positive: 239,
          True negative: 8,
          False positive: 241,
          False negative: 10
```

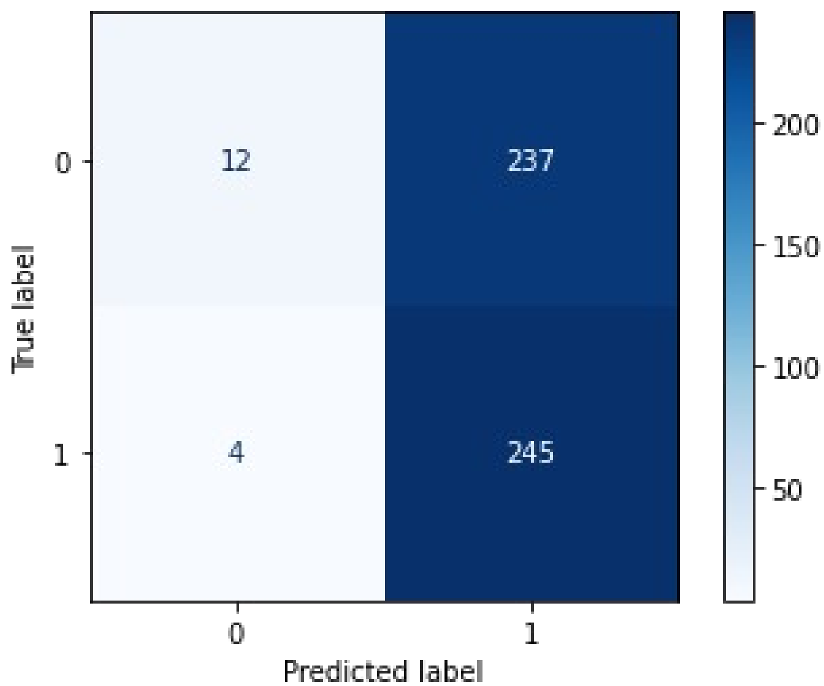



```
              precision    recall  f1-score   support

         0.0       0.44      0.03      0.06       249
         1.0       0.50      0.96      0.66       249

    accuracy                           0.50       498
   macro avg       0.47      0.50      0.36       498
weighted avg       0.47      0.50      0.36       498

test iteration = 11
start_date:570 , end_ft_day: 750        start_lbl_date:751 ,
end_lbl_day: 841

        Train results:
          True positive: 244,
          True negative: 10,
          False positive: 239,
          False negative: 5
```



	precision	recall	f1-score	support
0.0	0.67	0.04	0.08	249
1.0	0.51	0.98	0.67	249
accuracy			0.51	498
macro avg	0.59	0.51	0.37	498
weighted avg	0.59	0.51	0.37	498

```
test iteration = 12
start_date:600 , end_ft_day: 780        start_lbl_date:781 ,
end_lbl_day: 871

        Train results:
          True positive: 245,
          True negative: 12,
          False positive: 237,
          False negative: 4
```




```
              precision    recall  f1-score   support

         0.0       0.75      0.05      0.09       249
         1.0       0.51      0.98      0.67       249

    accuracy                           0.52       498
   macro avg       0.63      0.52      0.38       498
weighted avg       0.63      0.52      0.38       498
```

###Picking porfolio

wanting to get the best representation of the wanted date we will take the closet thing

```
all_features_train_df,all_labelling_train_df =
get_features_labels_from_full_dataframe(all_df,start_train_features_da
y = int(all_df['t0'].max()-270-200) )
features_df = all_features_train_df.copy()
monthly_features_df = Get_Monthly(all_features_train_df)
train_df = (
            calculate_featurs(all_features_train_df)
            .reset_index()
            .pipe(lambda d:Get_all_features(d, features_df,
monthly_features_df))
            .pipe(lambda d:add_actual(d,all_labelling_train_df))
            .rename(columns = {'actual_y':'target'})
            )
```

```
start_date:1051 , end_ft_day: 1231        start_lbl_date:1232 ,
end_lbl_day: 1322
```

```
clf = RandomForestClassifier(max_depth=3, random_state=0)
clf.fit(train_df.drop(['stock', 'target'],axis=1), train_df['target'])
```

```
RandomForestClassifier(max_depth=3, random_state=0)
```

```
all_features_test_df,all_labelling_train_df =
get_features_labels_from_full_dataframe(all_df,start_train_features_da
y = 1320  )
features_df2 = all_features_test_df.copy()
monthly_features_df2 = Get_Monthly(all_features_test_df)

test_df = (
          calculate_featurs(all_features_test_df)
          .reset_index()
          .pipe(lambda d:Get_all_features(d, features_df2,
monthly_features_df2))
          )
```

```
start_date:1320 , end_ft_day: 1500        start_lbl_date:1501 ,
end_lbl_day: 1591
```

```
all_df.sort_values('t0',ascending=False)
```

```
             Date        Open        High         Low       Close
Volume  \
521660 2022-08-31  157.454675  158.699101  155.513375  155.831940
2149000.0
143349 2022-08-31  273.049648  274.836222  268.009236  269.396606
3120200.0
235223 2022-08-31  201.868954  201.868954  196.237156  196.883911
1869300.0
278273 2022-08-31   28.759241   29.106933   28.183063   28.232733
5695500.0
347463 2022-08-31   41.040433   41.323265   40.143159   40.338219
13755400.0
...           ...         ...         ...         ...         ...
...
396711 2018-07-02   73.831568   75.000343   73.545337   75.000343
1389700.0
199871 2018-07-02  106.294437  106.950211  103.948779  104.873589
461700.0
9450   2018-07-02  127.033321  127.183883  125.546559  126.751022
662500.0
51450  2018-07-02   60.457115   61.061408   60.429225   60.670944
1026200.0
0      2018-07-02  165.049191  165.412283  163.402573  165.099854
1815500.0
```

```
        stock  Adj Close         dt      t0
521660   ZTS        NaN 2022-08-31  1521.0
143349   DHR        NaN 2022-08-31  1521.0
235223   HCA        NaN 2022-08-31  1521.0
278273  JNPR        NaN 2022-08-31  1521.0
347463   NEM        NaN 2022-08-31  1521.0
...      ...        ...        ...     ...
396711   PRU        NaN 2018-07-02     0.0
199871   FRT        NaN 2018-07-02     0.0
9450     AAP        NaN 2018-07-02     0.0
51450    AJG        NaN 2018-07-02     0.0
0        MMM        NaN 2018-07-02     0.0

[521661 rows x 10 columns]
```

```
X = test_df.drop(['stock'],axis=1).fillna(-999)

y_pred_prob = clf.predict_proba(X)
y_pred = clf.predict(X)


Best_predictions = (
                    test_df
                    .assign(certainty = y_pred_prob.max(axis=1),
                            target = y_pred )
                    .pipe(lambda
d:d.sort_values(by='certainty',ascending=False))
                    )
stocks_to_long = (
                  Best_predictions
                 .query('target == 1')
                 .head(50)
                 )

stocks_to_short = (
                  Best_predictions
                 .query('target == 0')
                 .head(50)
                 )

long = list(stocks_to_long['stock'].values)
long_df_features = features_df.query('stock in(@long)')

def std_of_portfolio(features_df):
  return  (
            features_df
            .groupby('stock')
            .apply(lambda x: calculate_returns(x))
            .reset_index()
            [0]
```

```
            .std()
            )

def get_sharp(features_df,rf=0):
  sumOpen = features_df.groupby('stock')['Open'].first().sum()
  sumClose = features_df.groupby('stock')['Close'].last().sum()
  IndexReturn = (100*(sumClose-sumOpen)/sumOpen).min()
  return (IndexReturn - rf)/std_of_portfolio(features_df)

def get_max_drawdown(features_df):

  # group the data by date and calculate the daily returns of the
index
  index_returns = features_df.groupby('dt').apply(lambda x:
(x['Close'].sum() - x['Open'].sum()) / x['Open'].sum())

  # calculate the cumulative returns of the index
  cumulative_returns = (1 + index_returns).cumprod()
  # calculate the running maximum of the cumulative returns
  running_max = cumulative_returns.cummax()

  # calculate the drawdown from the running maximum
  drawdown = cumulative_returns / running_max - 1

  # find the maximum drawdown of the index
  max_drawdown = drawdown.min()
  return max_drawdown

print(f'''
      sharp of portfolio is : {get_sharp(long_df_features)}
      Volatility of portfolio is :{std_of_portfolio(long_df_features)}
      The maximum drawdown of the portfolio is :
{get_max_drawdown(long_df_features):.2%}
      \n
      sharp of the S&P 500 index is : {get_sharp(features_df2)}
      Volatility of the S&P 500 index is:
{std_of_portfolio(features_df2)}
      The maximum drawdown of the S&P 500 index is
{get_max_drawdown(features_df2):.2%}")
      '''
      )


      sharp of portfolio is : 0.1216530727344285
      Volatility of portfolio is :14.269580574547849
      The maximum drawdown of the portfolio is : -9.13%


      sharp of the S&P 500 index is : -0.4164664950184792
      Volatility of the S&P 500 index is:17.924643548301763
```

```
    The maximum drawdown of the S&P 500 index is -13.41%")
```

We picked training the model on the most recent time we could in respect to the required date(01/06/2022), we wanted to both the train and the test to have the same length of time for calculating features(6 months) and for the train we still had to have a labelling period so we could calibrate our model.

this is all under the assumption of still using a basic RF model, in the real world we would try to use a more complex models such as LTSM or Transfomer based NN, which if was the case we would take a much larger period of training time

##Third Assignment

```
!pip3 install backtesting
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: backtesting in /usr/local/lib/python3.8/dist-packages (0.3.3)
Requirement already satisfied: pandas!=0.25.0,>=0.25.0 in /usr/local/lib/python3.8/dist-packages (from backtesting) (1.3.5)
Requirement already satisfied: numpy>=1.17.0 in /usr/local/lib/python3.8/dist-packages (from backtesting) (1.21.6)
Requirement already satisfied: bokeh>=1.4.0 in /usr/local/lib/python3.8/dist-packages (from backtesting) (2.3.3)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.8/dist-packages (from bokeh>=1.4.0->backtesting) (2.8.2)
Requirement already satisfied: packaging>=16.8 in /usr/local/lib/python3.8/dist-packages (from bokeh>=1.4.0->backtesting) (23.0)
Requirement already satisfied: Jinja2>=2.9 in /usr/local/lib/python3.8/dist-packages (from bokeh>=1.4.0->backtesting) (2.11.3)
Requirement already satisfied: PyYAML>=3.10 in /usr/local/lib/python3.8/dist-packages (from bokeh>=1.4.0->backtesting) (6.0)
Requirement already satisfied: typing-extensions>=3.7.4 in /usr/local/lib/python3.8/dist-packages (from bokeh>=1.4.0->backtesting) (4.5.0)
Requirement already satisfied: tornado>=5.1 in /usr/local/lib/python3.8/dist-packages (from bokeh>=1.4.0->backtesting) (6.2)
Requirement already satisfied: pillow>=7.1.0 in /usr/local/lib/python3.8/dist-packages (from bokeh>=1.4.0->backtesting) (7.1.2)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-packages (from pandas!=0.25.0,>=0.25.0->backtesting) (2022.7.1)
Requirement already satisfied: MarkupSafe>=0.23 in
```

```
/usr/local/lib/python3.8/dist-packages (from Jinja2>=2.9-
>bokeh>=1.4.0->backtesting) (2.0.1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.8/dist-packages (from python-dateutil>=2.1-
>bokeh>=1.4.0->backtesting) (1.15.0)
```

###3.1+3.2

```python
from backtesting import Backtest, Strategy
from backtesting.lib import crossover

from backtesting.test import SMA
from statistics import mean, stdev

class SmaCross(Strategy):
    n1 = 10
    n2 = 20

    def init(self):
        close = self.data.Close
        self.sma1 = self.I(SMA, close, self.n1)
        self.sma2 = self.I(SMA, close, self.n2)

    def next(self):
        if crossover(self.sma1, self.sma2):
            self.buy()
        elif crossover(self.sma2, self.sma1):
            self.sell()

def calculate_portfolio_stats(all_data, portfolio_stocks):
    '''
        all_data: pd.Dataframe, needs to include all your required
stocks OHLCV data.
        portfolio_stocks: List[str], list of your required portfolio
stock tickers for an example: ['AAPL','TSLA'].
        must be consistentr with the stocks column uin your all_data
df
    '''
    assert len(portfolio_stocks) > 1, 'portfolio must include more
than one stock'
    returns = []
    sharpes = []
    for stock in portfolio_stocks:
        if stock == 'A': continue
        stock_data = all_data[all_data['stock'] == stock][['Open',
'High', 'Low', 'Close', 'Volume']]
        bt = Backtest(stock_data, SmaCross,
                      cash=10000, commission=.002,
                      exclusive_orders=True)
        output = bt.run()
```

```
        sharpes.append(output.loc['Sharpe Ratio'])
        returns.append(output.loc['Return [%]'])
    mean_returns = mean(returns)
    returns_std = stdev(returns)
    mean_sharpes = mean(sharpes)
    sharpes_std = stdev(sharpes)
    return mean_returns, returns_std, mean_sharpes, sharpes_std


results_df =
pd.DataFrame([calculate_portfolio_stats(all_df.set_index('dt'),stocks_
to_short['stock'].values.tolist()),
calculate_portfolio_stats(all_df.set_index('dt'),stocks_to_long['stock
'].values.tolist()),
calculate_portfolio_stats(all_df.set_index('dt'),all_df.stock.unique()
.tolist())],
                  columns=['mean_returns', 'returns_std',
'mean_sharpes', 'sharpes_std'],
                  index=['short_portfolio', 'long_portfolio',
'entire_index'])
results_df
```

	mean_returns	returns_std	mean_sharpes	sharpes_std
short_portfolio	1.711490	78.315160	0.105826	0.178389
long_portfolio	-34.221876	41.924843	0.036592	0.130008
entire_index	-8.187407	78.901263	0.075192	0.159081