Part 1 Data Gathering

```
# Install the required packages
! pip install beautifulsoup4
! pip install yfinance
```

```
    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: requests>=2.26 in /usr/local/lib/python3.8/dist-packages (from yfinance) (2.28.2)
    Requirement already satisfied: html5lib>=1.1 in /usr/local/lib/python3.8/dist-packages (from yfinance) (1.1)
    Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.8/dist-packages (from yfinance) (1.22.4)
    Requirement already satisfied: beautifulsoup4>=4.11.1 in /usr/local/lib/python3.8/dist-packages (from yfinance) (4.11.2)
    Requirement already satisfied: pandas>=1.3.0 in /usr/local/lib/python3.8/dist-packages (from yfinance) (1.3.5)
    Requirement already satisfied: pytz>=2022.5 in /usr/local/lib/python3.8/dist-packages (from yfinance) (2022.7.1)
    Requirement already satisfied: cryptography>=3.3.2 in /usr/local/lib/python3.8/dist-packages (from yfinance) (39.0.1)
    Requirement already satisfied: lxml>=4.9.1 in /usr/local/lib/python3.8/dist-packages (from yfinance) (4.9.2)
    Requirement already satisfied: appdirs>=1.4.4 in /usr/local/lib/python3.8/dist-packages (from yfinance) (1.4.4)
    Requirement already satisfied: multitasking>=0.0.7 in /usr/local/lib/python3.8/dist-packages (from yfinance) (0.0.11)
    Requirement already satisfied: frozendict>=2.3.4 in /usr/local/lib/python3.8/dist-packages (from yfinance) (2.3.5)
    Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.8/dist-packages (from beautifulsoup4>=4.11.1->yfir
    Requirement already satisfied: cffi>=1.12 in /usr/local/lib/python3.8/dist-packages (from cryptography>=3.3.2->yfinance)
    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: webencodings in /usr/local/lib/python3.8/dist-packages (from html5lib>=1.1->yfinance) (0.5
    Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.8/dist-packages (from pandas>=1.3.0->yfir
    Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.8/dist-packages (from requests>=2.26->yfinanc
    Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.8/dist-packages (from requests>=2.26->y
    Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.8/dist-packages (from requests>=2.26->yfinance) (2.
    Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.8/dist-packages (from requests>=2.26->yfir
    Requirement already satisfied: pycparser in /usr/local/lib/python3.8/dist-packages (from cffi>=1.12->cryptography>=3.3.2-
```

```
from bs4 import BeautifulSoup as bs
import requests
import yfinance as yf
import pandas as pd
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import numpy as np
from scipy.stats import linregress
import matplotlib.pyplot as plt
import warnings
```

Get Stocks daily OCHLV data

- S&P get list of stocks from wikipedia
- Download data from yfinance

```
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
```

Download data from yfinance

```
all_df = pd.DataFrame()
start_date = '2018-07-01'
end_date = '2022-06-01'
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.to_csv(fname_string)
```

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```

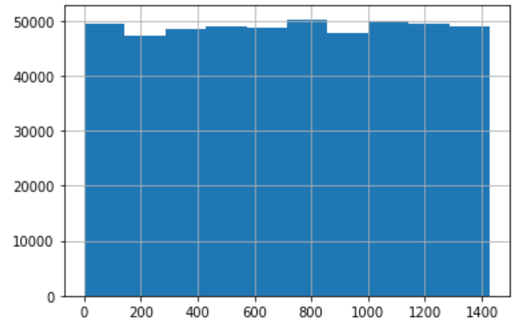
Read Locally and skip the download

```
all_df = pd.read_csv(fname_string)
```

```
all_df['dt'] = pd.to_datetime(all_df['Date'])
all_df['t0'] = (all_df['dt'] - all_df['dt'].min()).dt.days.astype(float)
```

```
all_df['t0'].hist()
```

```
<AxesSubplot:>
```



Calculate Features & Target values for all stocks

```
all_df['dt'] = pd.to_datetime(all_df['Date'])
all_df['t0'] = (all_df['dt'] - all_df['dt'].min()).dt.days.astype(float)

# Filter the DataFrame to keep only the stocks that were traded on all trading days
counts = all_df['stock'].value_counts()
all_days_stocks = counts[counts == counts.max()].index.tolist()
all_df = all_df[all_df['stock'].isin(all_days_stocks)]

# Split the data to segments (6 months features, 3 months labelling)
FEATURES_SIZE = 180
LABELLING_SIZE = 90

start_train_features_day = 0
end_train_features_day = start_train_features_day + FEATURES_SIZE
start_train_labelling_day = end_train_features_day + 1
end_train_labelling_day = start_train_labelling_day + LABELLING_SIZE
all_features_train_df = all_df[(all_df['t0'] >= start_train_features_day)&(all_df['t0'] < end_train_features_day)]
all_labelling_train_df = all_df[(all_df['t0'] >= start_train_labelling_day)&(all_df['t0'] < end_train_labelling_day)]
```

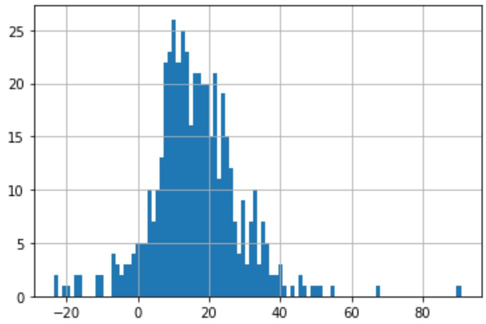
```
print(f'start_date:{start_train_features_day} , end_ft_day: {end_train_features_day}')
```

```
start_date:0 , end_ft_day: 180
```

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

```
#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)
```

```
<AxesSubplot:>
```




```
# Make sure that the features are 6 months
print(all_features_train_df['t0'].max() - all_features_train_df['t0'].min())
# Make sure that the labelling is 90 days
print(all_labelling_train_df['t0'].max() - all_labelling_train_df['t0'].min())
```

```
179.0
88.0
```

```
# 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

```
# average change during the day
def calculate_high_to_low(x):
  return 100*(x['High'] - x['Low'])/x['Open']
high_to_low_df = all_features_train_df.groupby('stock').apply(calculate_high_to_low).reset_index()
```

```
# Calculating the median of how much the stock has moved during the day
analysis_df = high_to_low_df.groupby('stock').median().reset_index().drop('level_1', axis =1)
analysis_df.columns = ['stock', 'median high to low']
```

```
analysis_df['change in price'] = train_returns.values
# Adding a binary target column for our classification based on the labelling
analysis_df.loc[analysis_df['stock'].isin(good),'target'] = 1
analysis_df['target'].fillna(0,inplace=True)
analysis_df
```

	stock	median high to low	change in price	target
0	A	1.778113	21.163696	1.0
1	AAL	3.351053	-0.758539	0.0
2	AAP	1.995692	9.319022	0.0
3	AAPL	2.061855	20.333478	1.0
4	ABBV	2.361385	-10.940559	0.0
...	...	...	...	...
486	YUM	1.336425	9.225094	0.0
487	ZBH	1.997741	24.167322	1.0
488	ZBRA	2.688361	33.399114	1.0
489	ZION	2.197801	12.829610	0.0
490	ZTS	1.603558	18.293441	1.0

491 rows × 4 columns

Chosen Feature:

Median high to low - the median of the daily high - low, it can indicate how stable the stock is.

```
corr = analysis_df['median high to low'].corr(analysis_df['change in price'])
print("correlation:", corr)

slope, intercept, r_value, p_value, std_err = linregress(analysis_df['median high to low'], analysis_df['change in price'])
print("linear regression:")
print("slope:", slope)
print("intercept:", intercept)
print("r-squared:", r_value**2)
plt.scatter(analysis_df['median high to low'], analysis_df['change in price'])

# Plot the regression line
x = analysis_df['median high to low']
y = slope*x + intercept
plt.plot(x, y, color='r')

# Add labels and title
plt.xlabel('median high to low')
plt.ylabel('change in price')
plt.title('Regression Plot')
# Show the plot
plt.show()
```

```
correlation: 0.2557578280417361
linear regression:
slope: 5.22010202482491
intercept: 5.512830620644616
r-squared: 0.06541206660462627
```


```
df1 = analysis_df[analysis_df['median high to low']>1.9]
df0 = analysis_df[analysis_df['median high to low']<=1.9]

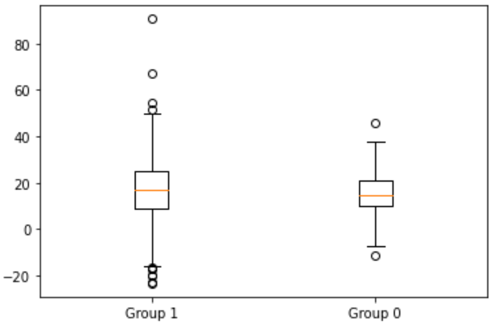
plt.boxplot([df1['change in price'], df0['change in price']], labels=['Group 1', 'Group 0'])
plt.show()
```

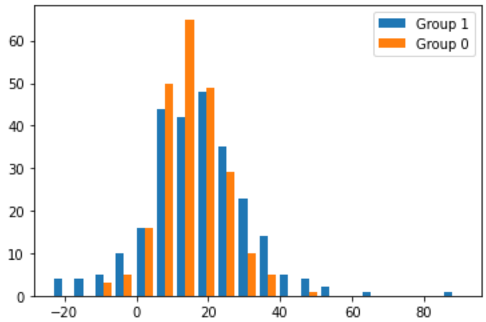
```
# Use histogram to visualize the distribution of the two groups
plt.hist([df1['change in price'], df0['change in price']], bins=20, label=['Group 1', 'Group 0'])
plt.legend()
plt.show()

# Calculate mean, median, 20% percentiles for each group
print("Group 1 mean: ", df1['change in price'].mean())
print("Group 1 median: ", df1['change in price'].median())
print("Group 1 20% percentile: ", df1['change in price'].quantile(0.2))

print("Group 0 mean: ", df0['change in price'].mean())
print("Group 0 median: ", df0['change in price'].median())
print("Group 0 20% percentile: ", df0['change in price'].quantile(0.2))

# Use skew and kurtosis to check the shape of the distributions
print("Group 1 Skewness: ", df1['change in price'].skew())
print("Group 1 Kurtosis: ", df1['change in price'].kurtosis())
print("Group 0 Skewness: ", df0['change in price'].skew())
print("Group 0 Kurtosis: ", df0['change in price'].kurtosis())
```






```
Group 1 mean:  17.16383159661539
Group 1 median:  16.82641199929448
Group 1 20% percentile:  7.456830983962064
Group 0 mean:  15.120723613420914
Group 0 median:  14.452638389998937
Group 0 20% percentile:  8.7318539215742
Group 1 Skewness:  0.4180592526654256
Group 1 Kurtosis:  2.751354510436931
Group 0 Skewness:  0.13216865302269487
Group 0 Kurtosis:  0.6474033914830333
```

```
true_positive = len(df1[df1['target'] == 1])
true_negative = len(df0[df0['target'] == 0])
false_positive = len(df1[df1['target'] == 0])
false_negative = len(df0[df0['target'] == 1])
print(
f'''
Train results:
  True positive: {true_positive},
  True negative: {true_negative},
  False positive: {false_positive},
  False negative: {false_negative}
''')

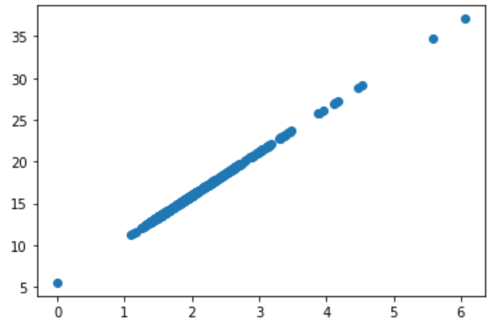
Precision = true_positive / (true_positive + false_positive)
Recall = true_positive / (true_positive + false_negative)
print("Precision:", Precision)
print("Recall:", Recall)
```

```
Train results:
  True positive: 139,
  True negative: 127,
  False positive: 119,
  False negative: 106
```

```
Precision: 0.5387596899224806
Recall: 0.5673469387755102
```

```
plt.scatter(analysis_df['median high to low'], y)
# The threshold chosen is 2.5
```

```
<matplotlib.collections.PathCollection at 0x7fd515158820>
```




```
df2 = analysis_df[analysis_df['median high to low']>2.5]
df3 = analysis_df[analysis_df['median high to low']<=2.5]

plt.boxplot([df3['change in price'], df2['change in price']], labels=['Group 3', 'Group 2'])
plt.show()

# Use histogram to visualize the distribution of the two groups
plt.hist([df3['change in price'], df2['change in price']], bins=20, label=['Group 3', 'Group 2'])
plt.legend()
plt.show()

# Calculate mean, median, 20% percentiles for each group
print("Group 3 mean: ", df3['change in price'].mean())
print("Group 3 median: ", df3['change in price'].median())
print("Group 3 20% percentile: ", df3['change in price'].quantile(0.2))
print("Group 2 mean: ", df2['change in price'].mean())
print("Group 2 median: ", df2['change in price'].median())
print("Group 2 20% percentile: ", df2['change in price'].quantile(0.2))

# Use skew and kurtosis to check the shape of the distributions
print("Group 3 Skewness: ", df3['change in price'].skew())
print("Group 3 Kurtosis: ", df3['change in price'].kurtosis())
print("Group 2 Skewness: ", df2['change in price'].skew())
print("Group 2 Kurtosis: ", df2['change in price'].kurtosis())
```

```
true_positive = len(df3[df3['target'] == 1])
true_negative = len(df2[df2['target'] == 0])
false_positive = len(df3[df3['target'] == 0])
false_negative = len(df2[df2['target'] == 1])
print(
f'''
Train results:
  True positive: {true_positive},
  True negative: {true_negative},
  False positive: {false_positive},
  False negative: {false_negative}
''')

Precision = true_positive / (true_positive + false_positive)
Recall = true_positive / (true_positive + false_negative)
print("Precision:", Precision)
print("Recall:", Recall)
```

```
Train results:
  True positive: 187,
  True negative: 28,
  False positive: 218,
  False negative: 58

Precision: 0.4617283950617284
Recall: 0.763265306122449

Group 3 20% percentile:  8.001505413098458
```

In summary, our goal was to predict stocks that would have high performance in the next 3 months. We found that linear regression alone was not effective in predicting the performance based on the feature values. Specifically, it did not accurately predict the value of the change. However, we did observe that linear regression could still indicate a trend. By setting a threshold, we found that the feature values were useful in generally predicting which stocks would perform better.

```
Group 2 Kurtosis:  2.5784814797114484
```

Training the model

```
features_df = all_features_train_df.copy()
features_df['month_index'] = (features_df['t0'] / 30).astype(int)

# monthly price feature
def calculate_price_change(x):
  return 100*(x.iloc[-1]['Close'] - x.iloc[0]['Open'])/x.iloc[0]['Open']

# volume feature
def calculate_volume_change(x):
  if x.iloc[0]['Volume'] == 0:
    return 0
  return abs(100*(x.iloc[-1]['Volume'] - x.iloc[0]['Volume'])/x.iloc[0]['Volume'])

# average daily change
def calculate_daily_returns(x):
  return 100*(x['Close'] - x['Open'])/x['Open']

# average change during the day
def calculate_high_to_low(x):
  return 100*(x['High'] - x['Low'])/x['Open']

# daily returns rank
def daily_returns_rank(x):
  return 1 if x['Close'] > x['Open'] else -1

# monthly price rank feature
def calculate_price_change(x):
  if x.iloc[-1]['Close'] - x.iloc[0]['Open'] < 0:
    return -1
  return 1


monthly_features_df = features_df.groupby(['stock','month_index']).apply(calculate_price_change).reset_index()
monthly_volume_df = features_df.groupby(['stock','month_index']).apply(calculate_volume_change).reset_index()
daily_change_df = features_df.groupby('stock').apply(calculate_daily_returns).reset_index()
high_to_low_df = features_df.groupby('stock').apply(calculate_high_to_low).reset_index()
features_df["daily rank"] = features_df.apply(daily_returns_rank, axis = 1)
monthly_rank_df = features_df.groupby(['stock','month_index']).apply(calculate_price_change).reset_index()
# Difference in volume
group_by_stock = features_df.groupby('stock')
max_volume = group_by_stock["Volume"].max()
```

```
min_volume = group_by_stock["Volume"].min()
volume_range = (max_volume-min_volume)/max_volume*100
# Monthly high to low difference
group_by_df = features_df.groupby(['stock','month_index'])
max_high = group_by_df["High"].max()
lowest_low = group_by_df["Low"].min()
hightolow = ((max_high-lowest_low)/max_high*100).groupby('stock').max()
# Monthly opens difference
max_open = abs(group_by_df["Open"].max())
lowest_open = abs(group_by_df["Open"].min())
open_dif = ((max_open-lowest_open)/max_open*100).groupby('stock').max()
# Monthly close difference
max_close = abs(group_by_df["Close"].max())
min_close = abs(group_by_df["Close"].min())
close_dif = ((max_close-min_close)/max_close*100).groupby('stock').max()
# 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']
# Calculating each stock max change in volume
max_positive_monthly_volume = monthly_volume_df.groupby('stock').max().reset_index()
train_df["highest change volume"] = max_positive_monthly_volume[0]
# Calculating median daily change
median_change = daily_change_df.groupby('stock').median().reset_index()
train_df["median"] = median_change[0]
# Calculating the median of how much the stock has moved during the day
median_high_to_low = high_to_low_df.groupby('stock').median().reset_index()
train_df["median high to low"] = median_high_to_low[0]
# Calaculating the rank for each stock according to when it finished the day higher or lower
df_sum = features_df.groupby('stock')['daily rank'].sum()
train_df = pd.merge(train_df, df_sum, on ='stock', how ='left')
# Calaculating the rank for each stock according to when it finished the month higher or lower
df_sum = monthly_rank_df.groupby('stock').sum()
train_df = pd.merge(train_df, df_sum[0], on ='stock', how ='left')
# Calaculating the precentage of change from higest to lowest volume
train_df = pd.merge(train_df, volume_range, on ='stock', how ='left')
# Calaculating the precentage of change from higest high to lowest low
train_df["monthly high to low"] = hightolow.values
# Calaculating the monthly open difference
train_df["open dif."] = open_dif.values
# Calaculating the monthly close difference
train_df["close dif."] = close_dif.values
train_df.columns = ['stock', 'best_month', 'worst_month', 'highest change volume', 'median', 'median high to low', 'daily rank
train_df.replace([np.inf, -np.inf], np.nan, inplace=True)
train_df.dropna(inplace=True)
# Adding a binary target column for our classification based on the labelling
train_df.loc[train_df['stock'].isin(good),'target'] = 1
train_df['target'].fillna(0,inplace=True)
train_df['target'].value_counts()
# 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=5, random_state=0)
x = train_df.drop(columns=['target','stock'], axis = 1)
clf.fit(x, train_df['target'])
# Training a Random Forest ML model to predict if the stock return will be above the median return in the labelling period
# based on best and worst month in the feature period
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(max_depth=5, random_state=0)
x = train_df.drop(columns=['target','stock'], axis = 1)
clf.fit(x, train_df['target'])
```

```
    RandomForestClassifier(max_depth=5, random_state=0)
```

Testing the model

- From the last day of the label dataset (180+90+start day)
- Start day: 270
- 12 cycles

```
def test(i):
  features_df = all_features_test_df.copy(deep=True)
  features_df = features_df.assign(month_index=(features_df['t0'] / 30).astype(int))
  monthly_features_df = features_df.groupby(['stock','month_index']).apply(calculate_returns).reset_index()
  monthly_volume_df = features_df.groupby(['stock','month_index']).apply(calculate_volume_change).reset_index()
  daily_change_df = features_df.groupby('stock').apply(calculate_daily_returns).reset_index()
  high_to_low_df = features_df.groupby('stock').apply(calculate_high_to_low).reset_index()
  monthly_rank_df = features_df.groupby(['stock','month_index']).apply(calculate_price_change).reset_index()
  worst_monthly_return = monthly_features_df.groupby('stock').min().reset_index()
```

```
    best_monthly_return = monthly_features_df.groupby('stock').max().reset_index()
    test_df = best_monthly_return[['stock',0]]
    test_df['worst'] = worst_monthly_return[0]
    test_df.columns = ['stock', 'best_month', 'worst_month']
    # Calculating each stock max change in volume
    max_positive_monthly_volume = monthly_volume_df.groupby('stock').max().reset_index()
    test_df["highest change volume"] = max_positive_monthly_volume[0]
    # Calculating median daily change
    median_change = daily_change_df.groupby('stock').median().reset_index()
    test_df["median"] = median_change[0]
    # Calculating the median of how much the stock has moved during the day
    median_high_to_low = high_to_low_df.groupby('stock').median().reset_index()
    test_df["median high to low"] = median_high_to_low[0]
    # Calaculating the rank for each stock according to when it finished the day higher or lower
    features_df["daily rank"] = features_df.apply(daily_returns_rank, axis = 1)
    df_sum = features_df.groupby('stock')['daily rank'].sum()
    test_df = pd.merge(test_df, df_sum, on ='stock', how ='left')
    # Calaculating the rank for each stock according to when it finished the month higher or lower
    monthly_rank_df = features_df.groupby(['stock','month_index']).apply(calculate_price_change).reset_index()
    df_msum = monthly_rank_df.groupby('stock').sum()
    test_df = pd.merge(test_df, df_msum[0], on ='stock', how ='left')
    # Calaculating the precentage of change from higest to lowest volume
    group_by_stock = features_df.groupby('stock')
    max_volume = group_by_stock["Volume"].max()
    min_volume = group_by_stock["Volume"].min()
    volume_range = (max_volume-min_volume)/max_volume*100
    test_df = pd.merge(test_df, volume_range, on ='stock', how ='left')
    # Calaculating the precentage of change from higest high to lowest low
    group_by_df = features_df.groupby(['stock','month_index'])
    max_high = group_by_df["High"].max()
    lowest_low = group_by_df["Low"].min()
    hightolow = ((max_high-lowest_low)/max_high*100).groupby('stock').max()
    test_df["monthly high to low"] = hightolow.values
    # Calaculating the monthly open difference
    max_open = abs(group_by_df["Open"].max())
    lowest_open = abs(group_by_df["Open"].min())
    open_dif = ((max_open-lowest_open)/max_open*100).groupby('stock').max()
    test_df["open dif."] = open_dif.values
    # Calaculating the monthly close difference
    max_close = abs(group_by_df["Close"].max())
    min_close = abs(group_by_df["Close"].min())
    close_dif = ((max_close-min_close)/max_close*100).groupby('stock').max()
    test_df["close dif."] = close_dif.values
    test_df.columns = ['stock', 'best_month', 'worst_month', 'highest change volume', 'median', 'median high to low', 'daily ran
    test_df.replace([np.inf, -np.inf], np.nan, inplace=True)
    test_df.dropna(inplace=True)
    test_df['predicted_y'] = clf.predict(test_df.drop(columns=['stock'], axis = 1))
    prediction=test_df['predicted_y']
    test_df['predicted_y'].value_counts()
    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()
    # Count the number of occurrences of each predicted label in the test data
    test_df.loc[:, 'predicted_y'].value_counts()
    test_returns = all_labelling_test_df.groupby('stock').apply(lambda x: calculate_returns(x))
    # Identify the stocks with returns above the median threshold
    label_threshold = test_returns.median()
    good_test = test_returns[test_returns > label_threshold].index
    # Assign a label of 1 to the actual_y column for the identified "good" stocks
    test_df.loc[test_df['stock'].isin(good_test), 'actual_y'] = 1
    test_df['actual_y'].fillna(0, inplace=True)
    # Count the number of occurrences of each actual label in the test data
    test_df['actual_y'].value_counts()

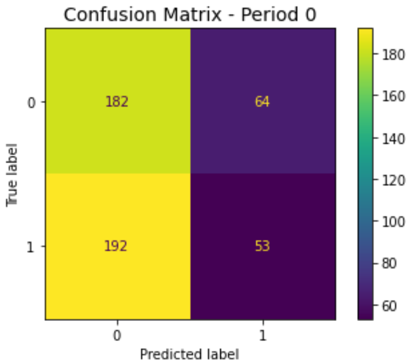
    if i<13:
      # Confusion matrix, precision, and recall
      true_positive = len(test_df[(test_df['predicted_y'] == test_df['actual_y'])&(test_df['predicted_y']==True)])
      true_negative = len(test_df[(test_df['predicted_y'] == test_df['actual_y'])&(test_df['predicted_y']==False)])
      false_positive = len(test_df[(test_df['predicted_y'] != test_df['actual_y'])&(test_df['predicted_y']==True)])
      false_negative = len(test_df[(test_df['predicted_y'] != test_df['actual_y'])&(test_df['predicted_y']==False)])
      print(
      f'''
      True positive: {true_positive},
      True negative: {true_negative},
      False positive: {false_positive},
      False negative: {false_negative}
      ''')
      matrix = confusion_matrix(test_df['actual_y'], test_df['predicted_y'])
      title = f"Confusion Matrix - Period {i}"
      disp = ConfusionMatrixDisplay(matrix, display_labels=[0, 1])
```

```
      disp.plot(cmap=plt.cm.viridis, xticks_rotation='horizontal')
      plt.title(title, fontsize=14)
      plt.show()

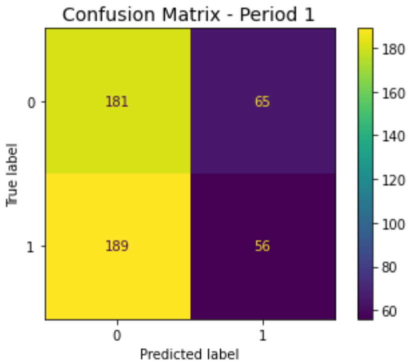
    return test_df
```

```
for i in range (12):
  start_test_features_day = start_train_features_day + 180 + i*30
  end_test_features_day = start_test_features_day + FEATURES_SIZE
  start_test_labelling_day = end_test_features_day + 1
  end_test_labelling_day = start_test_labelling_day + LABELLING_SIZE
  all_features_test_df = all_df[(all_df['t0'] >= start_test_features_day)&(all_df['t0'] < end_test_features_day)]
  all_labelling_test_df = all_df[(all_df['t0'] >= start_test_labelling_day)&(all_df['t0'] < end_test_labelling_day)]
  test(i)
```

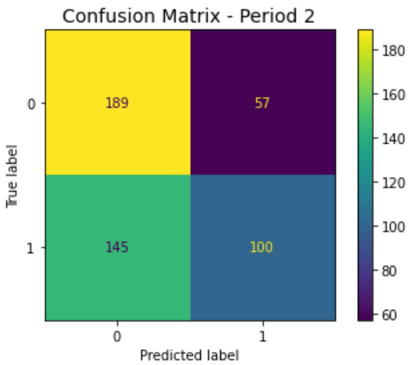
```
True positive: 53,
True negative: 182,
False positive: 64,
False negative: 192
```




```
True positive: 56,
True negative: 181,
False positive: 65,
False negative: 189
```




```
True positive: 100,
True negative: 189,
False positive: 57,
False negative: 145
```




```
True positive: 99,
True negative: 186,
False positive: 60,
False negative: 146
```