2_model_building_tuning_F3

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0.1 2_model_building_tuning_F3

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Description: We are trying to predict the retruns for 2 hours window.

- We are builing a basic model using the columns and the target provided in the intial dataset.
- Used Feature Set 3 which are basic features the data has.

0.1.1 Pre requisites:

1. And add the shortcut of the drive link : https://drive.google.com/drive/folders/1F8P3UlqSE6lFpHyBidVArd to your personal drive.

Files: crypto_data_hour_cleaned_v2.csv - Hourly Data

0.1.2 Output files:

Files:

0.2 Load and transform data

[ ]:
```
# Connecting to the google drive
from google.colab import drive
drive.mount('/content/drive')
from IPython.display import clear_output
```

```
Mounted at /content/drive
```

[ ]:
```
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np


from sklearn.model_selection import RandomizedSearchCV

#picking models for prediction.
```

```
from sklearn.svm import SVC
```

[ ]:
```
# file path
folder_path = '/content/drive/MyDrive/MADS_23_DL_final_project'
hour = pd.read_csv(folder_path + '/data/crypto_data_hour_cleaned_v2.csv')
```

[ ]:
```
hour.head()
```

[ ]:
```
             Open Time    Open    High     Low   Close   Volume train_test  \
0  2013-04-01 00:00:00  93.155  93.155  93.155  93.155   12.250      Train
1  2013-04-01 01:00:00  93.700  93.790  93.700  93.790   54.120      Train
2  2013-04-01 02:00:00  94.068  94.480  94.000  94.000  205.800      Train
3  2013-04-01 04:00:00  93.550  94.000  93.550  94.000    9.328      Train
4  2013-04-01 05:00:00  94.230  94.230  94.230  94.230    4.826      Train

  Crypto  pct_change_1hour  pct_change_2hour  pct_change_1day
0    BTC               NaN               NaN              NaN
1    BTC          0.006817               NaN              NaN
2    BTC          0.002239          0.009071              NaN
3    BTC          0.000000          0.002239              NaN
4    BTC          0.002447          0.002447              NaN
```

[ ]:
```
# drop columns
col_to_drop = ['pct_change_1hour','pct_change_1day']
only_2hour = hour[hour.columns.difference(col_to_drop)]
```

[ ]:
```
only_2hour.head()
```

[ ]:
```
    Close Crypto    High     Low    Open            Open Time   Volume  \
0  93.155    BTC  93.155  93.155  93.155  2013-04-01 00:00:00   12.250
1  93.790    BTC  93.790  93.700  93.700  2013-04-01 01:00:00   54.120
2  94.000    BTC  94.480  94.000  94.068  2013-04-01 02:00:00  205.800
3  94.000    BTC  94.000  93.550  93.550  2013-04-01 04:00:00    9.328
4  94.230    BTC  94.230  94.230  94.230  2013-04-01 05:00:00    4.826

   pct_change_2hour train_test
0               NaN      Train
1               NaN      Train
2          0.009071      Train
3          0.002239      Train
4          0.002447      Train
```

0.3 Generate Feature Engineering

0.3.1 Extract year, month, day, hour and weekday from time stamp

0.3.2 Encoding of ordinals

[ ]:
```
def encode_cyclicals(df_x):
    '''
    The function converts the date features encoded in the Sine and cosines.
    Input :
    df_x : Input data frame to be processed
    Output :
    df_x : processed dataframe.
    '''
      #"month","day","hour", "minute", "dayofweek"



      df_x['month_sin'] = np.sin(2*np.pi*df_x.month/12)
      df_x['month_cos'] = np.cos(2*np.pi*df_x.month/12)
      df_x.drop('month', axis=1, inplace=True)

      df_x['day_sin'] = np.sin(2*np.pi*df_x.day/31)
      df_x['day_cos'] = np.cos(2*np.pi*df_x.day/31)
      df_x.drop('day', axis=1, inplace=True)

      df_x['dayofweek_sin'] = np.sin(2*np.pi*df_x.weekday/7)
      df_x['dayofweek_cos'] = np.cos(2*np.pi*df_x.weekday/7)
      df_x.drop('weekday', axis=1, inplace=True)

      df_x['hour_sin'] = np.sin(2*np.pi*df_x.hour/24)
      df_x['hour_cos'] = np.cos(2*np.pi*df_x.hour/24)
      df_x.drop('hour', axis=1, inplace=True)

      df_x['hour_sin'] = np.sin(2*np.pi*df_x.minute/60)
      df_x['hour_cos'] = np.cos(2*np.pi*df_x.minute/60)
      df_x.drop('minute', axis=1, inplace=True)



      return df_x
```

[ ]:
```
# Extracting the Date details
df = only_2hour.copy()
df['year'] = pd.DatetimeIndex(df['Open Time']).year
df['month'] = pd.DatetimeIndex(df['Open Time']).month
df['day'] = pd.DatetimeIndex(df['Open Time']).day
df['weekday'] = pd.DatetimeIndex(df['Open Time']).dayofweek
```

```
df['Open Time'] = pd.to_datetime(df['Open Time'])
df['minute'] = df['Open Time'].dt.minute
df['hour'] = df['Open Time'].dt.hour
```

[ ]:
```
df.head(2)
```

[ ]:
```
    Close Crypto    High     Low    Open           Open Time  Volume  \
0  93.155    BTC  93.155  93.155  93.155 2013-04-01 00:00:00   12.25
1  93.790    BTC  93.790  93.700  93.700 2013-04-01 01:00:00   54.12

   pct_change_2hour train_test  year  month  day  weekday  minute  hour
0               NaN      Train  2013      4    1        0       0     0
1               NaN      Train  2013      4    1        0       0     1
```

[ ]:
```
# Transform the date details
df_v2 = encode_cyclicals(df.copy())
```

[ ]:
```
df = df_v2.copy()
```

0.3.3 One hot coding the coins

By this process we are tagging which record belongs which coin

[ ]:
```
# Applying one hot encoding on Crypto Coin

y_dummies = pd.get_dummies(df['Crypto'], prefix='Crypto', drop_first= False)
df_v2 = pd.concat([df, y_dummies], axis=1)
```

[ ]:
```
df_v2.head()
```

[ ]:
```
    Close Crypto    High     Low    Open           Open Time   Volume  \
0  93.155    BTC  93.155  93.155  93.155 2013-04-01 00:00:00   12.250
1  93.790    BTC  93.790  93.700  93.700 2013-04-01 01:00:00   54.120
2  94.000    BTC  94.480  94.000  94.068 2013-04-01 02:00:00  205.800
3  94.000    BTC  94.000  93.550  93.550 2013-04-01 04:00:00    9.328
4  94.230    BTC  94.230  94.230  94.230 2013-04-01 05:00:00    4.826

   pct_change_2hour train_test  year  …  Crypto_ADA  Crypto_BTC  Crypto_ETC  \
0               NaN      Train  2013  …           0           1           0
1               NaN      Train  2013  …           0           1           0
2          0.009071      Train  2013  …           0           1           0
3          0.002239      Train  2013  …           0           1           0
4          0.002447      Train  2013  …           0           1           0

   Crypto_ETH  Crypto_LINK  Crypto_LTC  Crypto_TRX  Crypto_XLM  Crypto_XMR  \
0           0            0           0           0           0           0
```

```
1            0           0           0           0           0           0
2            0           0           0           0           0           0
3            0           0           0           0           0           0
4            0           0           0           0           0           0

   Crypto_XRP
0            0
1            0
2            0
3            0
4            0

[5 rows x 28 columns]
```

[ ]:
```
df=df_v2.copy()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-af9227b74eeb> in <module>
----> 1 df=df_v2.copy()

NameError: name 'df_v2' is not defined
```

[ ]:
```
df.drop(['Crypto'], axis=1, inplace=True)
```

[ ]:
```
# creating a additional column if the model is used for new coin.
df['other_crypto'] =0
```

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

[ ]:
```
    Close    High     Low    Open           Open Time   Volume  \
0  93.155  93.155  93.155  93.155 2013-04-01 00:00:00   12.250
1  93.790  93.790  93.700  93.700 2013-04-01 01:00:00   54.120
2  94.000  94.480  94.000  94.068 2013-04-01 02:00:00  205.800
3  94.000  94.000  93.550  93.550 2013-04-01 04:00:00    9.328
4  94.230  94.230  94.230  94.230 2013-04-01 05:00:00    4.826

   pct_change_2hour train_test  year  month_sin  …  Crypto_BTC  Crypto_ETC  \
0               NaN      Train  2013   0.866025  …           1           0
1               NaN      Train  2013   0.866025  …           1           0
2          0.009071      Train  2013   0.866025  …           1           0
3          0.002239      Train  2013   0.866025  …           1           0
4          0.002447      Train  2013   0.866025  …           1           0

   Crypto_ETH  Crypto_LINK  Crypto_LTC  Crypto_TRX  Crypto_XLM  Crypto_XMR  \
0           0            0           0           0           0           0
```

```
1            0             0            0            0            0            0
2            0             0            0            0            0            0
3            0             0            0            0            0            0
4            0             0            0            0            0            0

   Crypto_XRP  other_crypto
0           0             0
1           0             0
2           0             0
3           0             0
4           0             0

[5 rows x 28 columns]
```

[ ]:
```
df['pct_change_2hour'].describe()
```

[ ]:
```
count    494730.000000
mean          0.001408
std           0.450256
min          -0.999995
25%          -0.006720
50%           0.000000
75%           0.007028
max         222.716582
Name: pct_change_2hour, dtype: float64
```

0.3.4 Defining the Target Variable.

We want to follow the classification approach and hence based on the "pct_change_2hour" we are creating 3 classes one class '0' when the returns are negative and '1' When the retruns are postive.

Finally, 2 when the returns beat the market value.

[ ]:
```
market_RoR = 26.89
market_RoR_2h = market_RoR/(365*12)
```

[ ]:
```
df['Target'] = np.where(df['pct_change_2hour']>0, 1,0)

df['Target'] = np.where(df['pct_change_2hour']>market_RoR_2h, 2,1)

df['Target'][df['Target']==1] = np.
 ↪where(df['pct_change_2hour'][df['Target']==1]>=0, 1,0)
```

[ ]:
```
df['Target'].value_counts(normalize=True)
```

[ ]:
```
0    0.435521
1    0.296079
2    0.268400
```

```
Name: Target, dtype: float64
```

```
[ ]: # dropping the column as we already extracted the target
     df.drop(['pct_change_2hour'], axis=1, inplace=True)
```

```
[ ]: df.columns
```

```
[ ]: Index(['Close', 'High', 'Low', 'Open', 'Open Time', 'Volume', 'train_test',
            'year', 'month_sin', 'month_cos', 'day_sin', 'day_cos', 'dayofweek_sin',
            'dayofweek_cos', 'hour_sin', 'hour_cos', 'Crypto_ADA', 'Crypto_BTC',
            'Crypto_ETC', 'Crypto_ETH', 'Crypto_LINK', 'Crypto_LTC', 'Crypto_TRX',
            'Crypto_XLM', 'Crypto_XMR', 'Crypto_XRP', 'other_crypto', 'Target'],
           dtype='object')
```

```
[ ]: df.shape
```

```
[ ]: (494732, 28)
```

0.4 Train / Test Split

```
[ ]: df['train_test'].value_counts()
```

```
[ ]: Train    407870
     Test      86862
     Name: train_test, dtype: int64
```

```
[ ]: # train test split
     train_df = df[df['train_test']=='Train']
     test_df = df[df['train_test']=='Test']
```

```
[ ]: train_df.head()
```

```
[ ]:     Close    High     Low    Open           Open Time   Volume train_test  \
     0  93.155  93.155  93.155  93.155 2013-04-01 00:00:00   12.250      Train
     1  93.790  93.790  93.700  93.700 2013-04-01 01:00:00   54.120      Train
     2  94.000  94.480  94.000  94.068 2013-04-01 02:00:00  205.800      Train
     3  94.000  94.000  93.550  93.550 2013-04-01 04:00:00    9.328      Train
     4  94.230  94.230  94.230  94.230 2013-04-01 05:00:00    4.826      Train

        year  month_sin  month_cos  …  Crypto_ETC  Crypto_ETH  Crypto_LINK  \
     0  2013   0.866025       -0.5  …           0           0            0
     1  2013   0.866025       -0.5  …           0           0            0
     2  2013   0.866025       -0.5  …           0           0            0
     3  2013   0.866025       -0.5  …           0           0            0
     4  2013   0.866025       -0.5  …           0           0            0

        Crypto_LTC  Crypto_TRX  Crypto_XLM  Crypto_XMR  Crypto_XRP  other_crypto  \
     0           0           0           0           0           0             0
```

```
1     0     0     0     0     0     0
2     0     0     0     0     0     0
3     0     0     0     0     0     0
4     0     0     0     0     0     0

   Target
0       0
1       0
2       2
3       1
4       1

[5 rows x 28 columns]
```

[ ]:
```
train_df.columns
```

[ ]:
```
Index(['Close', 'High', 'Low', 'Open', 'Open Time', 'Volume', 'train_test',
       'year', 'month_sin', 'month_cos', 'day_sin', 'day_cos', 'dayofweek_sin',
       'dayofweek_cos', 'hour_sin', 'hour_cos', 'Crypto_ADA', 'Crypto_BTC',
       'Crypto_ETC', 'Crypto_ETH', 'Crypto_LINK', 'Crypto_LTC', 'Crypto_TRX',
       'Crypto_XLM', 'Crypto_XMR', 'Crypto_XRP', 'other_crypto', 'Target'],
      dtype='object')
```

0.4.1 dropping the columns

[ ]:
```
target = train_df['Target']
train_df.drop(['Target','Open Time','train_test',],axis=1,inplace=True)
```

[ ]:
```
test_target = test_df['Target']
test_df.drop(['Target','Open Time','train_test',],axis=1,inplace=True)
```

[ ]:
```
norm_train_df = train_df.fillna(0)
```

[ ]:
```
# dropping the listof the columns
drop_columns = []
# drop_columns = ['Open','High', 'Low','Close']


if drop_columns:
  norm_train_df = train_df.drop(drop_columns,axis=1)
  norm_test_df = test_df.drop(drop_columns,axis=1)
else:
  norm_train_df = train_df
  norm_test_df = test_df
```

[ ]:
```
norm_test_df.columns
```

[ ]: Index(['Close', 'High', 'Low', 'Open', 'Volume', 'year', 'month_sin',
       'month_cos', 'day_sin', 'day_cos', 'dayofweek_sin', 'dayofweek_cos',
       'hour_sin', 'hour_cos', 'Crypto_ADA', 'Crypto_BTC', 'Crypto_ETC',
       'Crypto_ETH', 'Crypto_LINK', 'Crypto_LTC', 'Crypto_TRX', 'Crypto_XLM',
       'Crypto_XMR', 'Crypto_XRP', 'other_crypto'],
      dtype='object')

[ ]:
```
norm_train_df.shape
```

[ ]: (407870, 25)

[ ]:
```
target.shape
```

[ ]: (407870,)

[ ]:
```
def generate_model_report(y_actual, y_predicted, metric_type):
    print("=================Printing the {} metrics==================".
 ↪format(metric_type))
    print("Accuracy = " , accuracy_score(y_actual, y_predicted))
    print("Precision = " ,precision_score(y_actual, y_predicted,␣
 ↪average=metric_type))
    print("Recall = " ,recall_score(y_actual, y_predicted, average=metric_type))
    print("F1 Score = " ,f1_score(y_actual, y_predicted, average=metric_type))
    print("======================================")
```

1 DummyPredictor

The baseline Model which others model should be beating.

[ ]:
```
from sklearn.dummy import DummyClassifier

dummy_model = DummyClassifier(strategy='prior')

dummy_model.fit(train_df.fillna(0), target)
```

[ ]: DummyClassifier()

[ ]:
```
dummy_pred = dummy_model.predict(norm_test_df)
```

[ ]:
```
generate_model_report(test_target, dummy_pred, 'micro')
generate_model_report(test_target, dummy_pred, 'macro')
generate_model_report(test_target, dummy_pred, 'weighted')

from sklearn.metrics import classification_report
print('\nClassification Report\n')
print(classification_report(test_target, dummy_pred))
```

```
=================Printing the micro metrics==================
Accuracy =  0.4530289424604545
Precision =  0.4530289424604545
Recall =  0.4530289424604545
F1 Score =  0.45302894246045455
=====================================
=================Printing the macro metrics==================
Accuracy =  0.4530289424604545
Precision =  0.15100964748681817
Recall =  0.3333333333333333
F1 Score =  0.20785497531949956
=====================================
=================Printing the weighted metrics==================
Accuracy =  0.4530289424604545
Precision =  0.2052352227068378
Recall =  0.4530289424604545
F1 Score =  0.2824929589624103
=====================================

Classification Report

              precision    recall  f1-score   support

           0       0.45      1.00      0.62     39351
           1       0.00      0.00      0.00     25122
           2       0.00      0.00      0.00     22389

    accuracy                           0.45     86862
   macro avg       0.15      0.33      0.21     86862
weighted avg       0.21      0.45      0.28     86862
```

[ ]:

[ ]:

2 Random forest classifier

- feature importance test: https://machinelearningmastery.com/feature-selection-time-series-forecasting-python/

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=1000,␣
  ↪random_state=1,max_depth=15,n_jobs=-1)
model.fit(norm_train_df.fillna(0), target)
```

[ ]:
```
RandomForestClassifier(max_depth=15, n_estimators=1000, n_jobs=-1,
                       random_state=1)
```

[ ]:
```
predicted_values = model.predict(norm_test_df)
```

[ ]:
```
generate_model_report(test_target, predicted_values, 'micro')
generate_model_report(test_target, predicted_values, 'macro')
generate_model_report(test_target, predicted_values, 'weighted')
```

```
==================Printing the micro metrics===================
Accuracy =  0.485459694688126
Precision =  0.485459694688126
Recall =  0.485459694688126
F1 Score =  0.485459694688126
=====================================
==================Printing the macro metrics===================
Accuracy =  0.485459694688126
Precision =  0.47763856360398754
Recall =  0.38813840939033534
F1 Score =  0.3387030481265691
=====================================
==================Printing the weighted metrics===================
Accuracy =  0.485459694688126
Precision =  0.48107533612472375
Recall =  0.485459694688126
F1 Score =  0.3939975764718906
=====================================
```

[ ]:
```
from sklearn.metrics import classification_report
print('\nClassification Report\n')
print(classification_report(test_target, predicted_values))
```

```

Classification Report

              precision    recall  f1-score   support

           0       0.48      0.92      0.63     39351
           1       0.56      0.18      0.27     25122
           2       0.39      0.07      0.11     22389

    accuracy                           0.49     86862
   macro avg       0.48      0.39      0.34     86862
weighted avg       0.48      0.49      0.39     86862
```

[ ]:
```

```

[ ]:
```
print(model.feature_importances_)
```

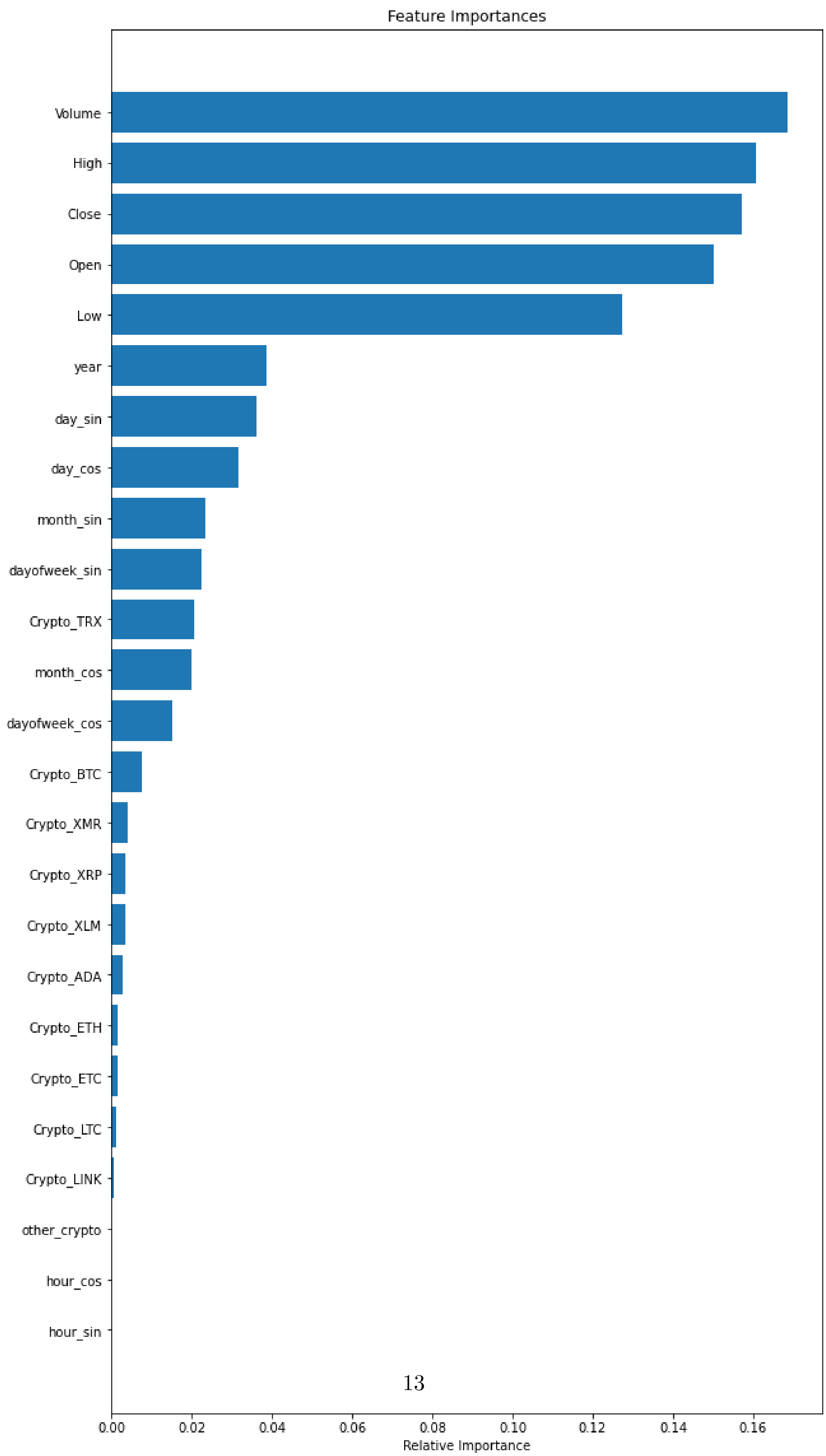
```
[0.15721451 0.16059549 0.12727058 0.150096   0.16870957 0.03866314
 0.02351456 0.02007184 0.03606777 0.03182576 0.02242277 0.01534457
 0.         0.         0.0030177  0.0075188  0.00167996 0.00169029
 0.00076409 0.00136469 0.02079332 0.00349603 0.00426099 0.00361756
 0.        ]
```

2.0.1 Ploting the Feature Importance

[ ]:
```
features=norm_train_df.columns
importances = model.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(10,20))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices])
plt.yticks(range(len(indices)), features[indices])
plt.xlabel('Relative Importance')
```

[ ]:
```
Text(0.5, 0, 'Relative Importance')
```


Feature Importances
Volume
High
Close
Open
Low
year
day_sin
day_cos
month_sin
dayofweek_sin
Crypto_TRX
month_cos
dayofweek_cos
Crypto_BTC
Crypto_XMR
Crypto_XRP
Crypto_XLM
Crypto_ADA
Crypto_ETH
Crypto_ETC
Crypto_LTC
Crypto_LINK
other_crypto
hour_cos
hour_sin
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
Relative Importance

```
[ ]: data = pd.DataFrame(columns=['features', "rf_feature_imp"])

     data['features'] = norm_train_df.columns
     data['rf_feature_imp'] = model.feature_importances_
```

3 Light Gradient Boosting Model

Ref: https://lightgbm.readthedocs.io/en/v3.3.2/

```
[ ]: import lightgbm as lgb
     unnorm_lgbm = lgb.LGBMClassifier(importance_type='gain')
     unnorm_lgbm.fit(norm_train_df.fillna(0), target)
```

```
[ ]: LGBMClassifier(importance_type='gain')
```

```
[ ]: lgbm_pred=unnorm_lgbm.predict(norm_test_df)
```

```
[ ]: generate_model_report(test_target, lgbm_pred, 'micro')
     generate_model_report(test_target, lgbm_pred, 'macro')
     generate_model_report(test_target, lgbm_pred, 'weighted')

     from sklearn.metrics import classification_report
     print('\nClassification Report\n')
     print(classification_report(test_target, lgbm_pred))
```

```
==================Printing the micro metrics===================
Accuracy =  0.4876816099099721
Precision =  0.4876816099099721
Recall =  0.4876816099099721
F1 Score =  0.4876816099099721
=====================================
==================Printing the macro metrics===================
Accuracy =  0.4876816099099721
Precision =  0.47276355074097487
Recall =  0.3890493933966081
F1 Score =  0.3356998825239719
=====================================
==================Printing the weighted metrics===================
Accuracy =  0.4876816099099721
Precision =  0.4774011462167295
Recall =  0.4876816099099721
F1 Score =  0.39276186225566
=====================================

Classification Report
```

```
              precision    recall  f1-score   support

           0       0.48      0.93      0.64     39351
           1       0.55      0.19      0.29     25122
           2       0.38      0.05      0.08     22389

    accuracy                           0.49     86862
   macro avg       0.47      0.39      0.34     86862
weighted avg       0.48      0.49      0.39     86862
```

3.0.1 Feature Importance

[ ]:
```
feature_importances = (unnorm_lgbm.feature_importances_ / sum(unnorm_lgbm.
 ↪feature_importances_))
temp_df = pd.DataFrame({'LGBM_feature_imp':feature_importances,'features':
 ↪norm_train_df.columns}).sort_values(by="LGBM_feature_imp",ascending=False)
temp_df
```

[ ]:

	LGBM_feature_imp	features
1	0.319765	High
3	0.181994	Open
4	0.177674	Volume
0	0.090327	Close
5	0.086725	year
6	0.024949	month_sin
2	0.021518	Low
15	0.021501	Crypto_BTC
22	0.021111	Crypto_XMR
7	0.012460	month_cos
23	0.011661	Crypto_XRP
8	0.007182	day_sin
9	0.005139	day_cos
10	0.004264	dayofweek_sin
14	0.003353	Crypto_ADA
11	0.002502	dayofweek_cos
21	0.002444	Crypto_XLM
20	0.001536	Crypto_TRX
19	0.001350	Crypto_LTC
17	0.001270	Crypto_ETH
18	0.000703	Crypto_LINK
16	0.000571	Crypto_ETC
12	0.000000	hour_sin
13	0.000000	hour_cos
24	0.000000	other_crypto

```
[ ]: data = data.merge(temp_df, on='features')
```

```
[ ]: data.sort_values(['rf_feature_imp', 'LGBM_feature_imp'], ascending=False)
```

[ ]:

	features	rf_feature_imp	LGBM_feature_imp
4	Volume	0.168710	0.177674
1	High	0.160595	0.319765
0	Close	0.157215	0.090327
3	Open	0.150096	0.181994
2	Low	0.127271	0.021518
5	year	0.038663	0.086725
8	day_sin	0.036068	0.007182
9	day_cos	0.031826	0.005139
6	month_sin	0.023515	0.024949
10	dayofweek_sin	0.022423	0.004264
20	Crypto_TRX	0.020793	0.001536
7	month_cos	0.020072	0.012460
11	dayofweek_cos	0.015345	0.002502
15	Crypto_BTC	0.007519	0.021501
22	Crypto_XMR	0.004261	0.021111
23	Crypto_XRP	0.003618	0.011661
21	Crypto_XLM	0.003496	0.002444
14	Crypto_ADA	0.003018	0.003353
17	Crypto_ETH	0.001690	0.001270
16	Crypto_ETC	0.001680	0.000571
19	Crypto_LTC	0.001365	0.001350
18	Crypto_LINK	0.000764	0.000703
12	hour_sin	0.000000	0.000000
13	hour_cos	0.000000	0.000000
24	other_crypto	0.000000	0.000000

3.0.2 Saving the feature importance for the Future use

```
[ ]: temp_file_path = '/content/drive/MyDrive/MADS_23_DL_final_project/notebooks/
     ↪chaitanya_temp_files'
     data.to_csv(temp_file_path +"/random_forest_2h_3class_feature_3.csv",␣
     ↪index=True)
```

#####Note:

This Notebooks we have build models which are baseline for our future models where we will be adding additional useful features to the model.

4 End of the Notebook

```
[ ]:
```

```
[ ]:
```